

Wireless Sensor Networks in the Era of IoT and Next-Generation Networks: A Comprehensive Survey on Energy Efficiency, Security Challenges, and AI-Driven Optimization

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ABSTRACT:

The WSNs now form one of the backbones of IoT, supporting its application areas in healthcare, environmental consideration, industrial automation and smart cities. However, these WSNs face various challenges, such as energy limitations, data handling issues, security vulnerability issues, and connectivity issues. This survey covers in-depth discussions on advances, challenges, and future directions in WSNs, emphasizing the integration of emerging technologies with Internet of Things (IoT), 5G/6G networks, machine learning (ML), and energy harvesting techniques. ML plays a role in optimizing data aggregation, fault detection, localization, and energy, while AI-based solutions are explored for network performance enhancement. On the other hand, energy harvesting techniques-solar energy, thermoelectric generation, and mechanical energy harvesting-are scrutinized as eco-sustainable ways to enhance the long-lasting capabilities of WSNs. Aspects of WSN integration with 5G/6G are covered, particularly ultra-low latency, dependability for real-time applications. Security-related challenges, including Jamming, Denial-of-sleep, and Routing attacks, have also been studied with proposed countermeasures against them. Future research directions, such as lightweight algorithms, support for mobility, edge computing, and fog computing integration to mitigate computation and energy constraints, have also been identified in the work. In doing so, it integrates the existing research while

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identifying gaps that serve as a roadmap to the efficient, secure, and scalable development of WSN systems, thus opening up further collaboration across discipline to fully realize them in real-world applications.

Keywords: Wireless Sensor Networks (WSNs); Internet of Things (IoT); Machine Learning (ML); Energy Harvesting in WSNs; 5G/6G Integration.

1. Introduction

The Sensor nodes are so-called devices connected into the networks with sensing, processing, and communication. They monitor the environment, perform computation, and communicate. By placing the latter in a specific area, sensor nodes would analyze data collected from that area and communicate with other nodes or a base station. The base station is responsible for controlling the operations of the network and is much more energy, computation, and communication resources (Yick et al., 2008). Firstly developed for various applications, WSNs are nowadays an important part of IoT. Today they provide service to a wide variety of sectors, like urban management, industrial activities, environmental monitoring, and e-health (Kandris et al., 2020). Operating difficulties to be faced by WSNs are in fact pretty many. One of the key concerns is the scant energy supply that sensor nodes have. Such batteries are difficult or impossible to repair or recharge, given their sometimes remote locations. Thus, the emphasis on fuel cell research is inspired by the importance of sustainability and energy conservation (Evangelakos et al., 2022). And the processing and storage capacities of these sensor nodes are quite limited, which set data handling as an important research issue (Wang & Liu, 2011). WSN operations become even more complicated because of the inevitable limitations of wireless communication such as transmission power, speed, channel capacity, interferers, and security threats (Rappaport, 2024). Additional challenges that occur when many sensor nodes are integrated into WSN are: connectivity preservation while coverage optimization (Al-Karaki & Gawanmeh, 2017), congestion prevention (Ploumis et al., 2012), service quality assurance (Kaur & Kumar, 2020), securing (Yu et al., 2020),

data aggregation (Sirsikar & Anavatti, 2015), fault tolerance (Adday et al., 2022), and node localization (Paul & Sato, 2017). To optimize performance in WSN, many objectives are usually going to be dealt with, thus the need for multi-objective optimization techniques (Singh et al., 2021).

These new knowledge and technologies, such as IoT (Shahraki et al., 2021), ML (Jiang et al., 2017), deep learning (Qiu et al., 2024), big data (Dai et al., 2019), 5G (Sufyan et al., 2023), edge computing, energy harvesting (Wang et al., 2023), and wireless power transfer (Huda et al., 2022), are all said to be powerful enough to improve WSN performance and potentially create new areas of research.

1.1 Aim

This work aims to offer an overview of the advancements and challenges, as well as future directions in WSNs, specifically concerning their integration with emerging technologies like the IoT, 5G/6G networks, machine learning, and energy harvesting techniques. The study intends to look into the transition of WSNs from limited applications to present-day actors in various domains such as health care, environmental monitoring, and industrial automation. Furthermore, the work aims to develop solutions and also promote WSN potential toward sustainable and intelligent systems, considering the key challenges of energy efficiency and data handling, security, and connectivity. It will also discuss AI and ML in boosting WSN performance and the convergence of WSNs with IoT and 5G/6G networks for ultra-low latency and reliability. Eventually, the study is expected to provide a runway for future research and development on WSNs with interdisciplinary approaches to

overcome the current constraints and unleash new opportunities.

1.2 Scope

In a more linearly progressive manner, it spells out an exhaustive and critical analysis of various architectures of WSNs, energy-efficient techniques, ML applications, and new trends like fog and edge computing and energy harvesting. It will avow-to-cover integration of such WSNs with IoT and 5G/6G networks-for-that-purpose-applications: smart cities, precision agriculture, health, and industrial automation. Critical issues in WSNs such as energy limitations, data aggregation, fault tolerance, security, and localization shall especially be discussed. The application of AI and ML in enhancing the performance of WSNs, facilitating real-time decision-making, and improving network efficiency is also part of the scope. This study forecasts the trends, including lighter weight algorithms, mobility support, and the merger with state-of-the-art computing paradigms such as edge and fog computing. This work will give a holistic perspective of the current state and future possibilities of WSNs by combining all past research with gaps in existing research.

1.3 Contributions

The all-in-one Comprehensive Review: detailed examination of WSN architectures, energy efficiency strategies, and new technologies; a well-rounded picture of what advancements and challenges are all about;

2. Process of review

The current literature review is a consolidated appraisal of works that deal with WSNs either alone or in conjunction with the latest technologies, such as the Internet of Things (IoT), generation 5 onwards and higher (5G/6G), machine learning, and energy harvesting techniques. The review period of nearly sixteen years, from 2008 to 2024, gives an all-embracing, contemporaneous outlook on progress and challenges faced relating to WSNs. The work covered in this review was selected for relevance to wider areas like WSN architecture, energy efficiency, security, applications related to

- Emerging Technologies Integration: WSN incorporated in the exploration of IoT; integration with 5G/6G networks and AI/ML, where the goal is improving networking performance and allowing intelligent systems.
- Energy Efficiency Solutions: Analysis of energy harvesting alternatives, renewable energy options, and power management schemes as energy constraints for WSNs.
- Machine Learning Applications: Supervised, unsupervised, and reinforcement learning methods for data aggregation, fault detection, localization, and energy optimization for WSN discussion
- Security and Privacy: An examination of security in the wireless sensor networks, recommended solutions, such as intrusion detection systems and secure routing protocols.
- Future Directions: This identifies the research gaps and upcoming trends in such topics as mobility support, lightweight algorithms, and integration with edge and fog computing.
- Interdisciplinary Approach: Need to work between material science, nanotechnology, and electronics to produce efficient and reliable systems in WSN.
- Applications in Practice: show how WSNs can transform health care, environmental monitoring, industrial automation, and smart cities.

machine learning, coupled with integration into IoT and 5G networks. In all, 163 references were reviewed from a wide range of publishers such as IEEE, Springer, Elsevier, ACM, MDPI, and so on. The review encompasses work presented at conferences and published in journals so as to allow for a well-balanced outline of theoretical versus applied development. Below are some statistics that give a detailed breakdown of the selection process, including time frame involved, number of papers, and publication sources. Table 1 displays details of the reviewed paper, and Fig 1 shows the year-wise review paper used.

3. WSN Architecture

Typical WSN architecture designs include a sensing field containing different sensor nodes, such as data-sensing nodes, a base station, and a sink node, all interconnected with one another. In the sensing field, the base station collects data from the sensor nodes and passes it over to sink node. Sink node then collects the data from all the sensor readings effortlessly, owing to its high processing function and memory capacity. Every sensor node is made up of several basic components including a sensing unit, a microcontroller, a wireless transceiver, and a battery, all of which are relevant in detecting physical objects. The microcontroller captures the data of the sensing unit as digitized by the microcontroller whose other functions include processing and coordination. The resulting digitized data is sent to other interconnected sensor nodes through the transceiver that transmits and receives data. Based on the qualities of the sensor nodes, WSNs are classified into four types: static, mobile, hybrid and mobile robot. Static-WSN deploy sensors that do not move. Mobile-WSN, on the other hand, require sensors that are placed on movable platforms and can be relocated later on after the initial deployment. Hybrid-WSN combine both static and mobile sensors. In some cases, robots are employed to manage static sensors, forming Wireless Sensor and Robot Networks (WSRNs). In WSRNs, robots carry static sensors as payload and deploy them in optimal locations, often using route optimization algorithms to enhance mobility. Battery power is crucial for all stages of data communication, enabling users to access data and information via the internet as needed. Figure 1 illustrates the typical network architecture of sensor nodes in a WSN.

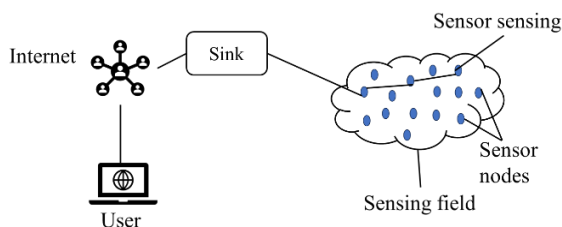


Figure 1. Structure of the WSN

Data transmission in WSNs is facilitated by routing protocols, which are critical for prolonging network

lifespan. Consequently, significant emphasis is placed on designing these protocols to be energy-efficient and tailored to application requirements. There are two main types of data collection protocols: hierarchical and non-hierarchical. Non-hierarchical protocols offer the advantage of direct event transmission between layers without intermediary processing, which is common in other communication systems. Nodes are typically drawn to the sink node, ensuring they remain within transmission range. Non-hierarchical WSNs are ideal for event-driven data models, while hierarchical architectures are better suited for long-term deployments. Hierarchical routing provides broader coverage, whereas geographic routing extends network life. A hybrid approach, where power-intensive tasks are handled by a more capable node, is often advisable. Hierarchical routing can be further classified into four principal categories: chain-based routing, tree-based routing, grid-based routing, and cluster-based routing. Chain-based routing involves a simple implementation and management with a stable chain structure where nodes transmit data to the closest one, effectively conserving energy. However, it incurs delays when a distance sensor node is far away from the sink node and hence is not quite suitable for time-sensitive applications. In tree-based routing, nodes are arranged into branches, and data is transmitted from the leaf nodes to their parent nodes, eventually reaching the sink node. The major disadvantage of tree-based routing is that if a parent node fails, data transfer through its branch would cease. Branches having many sensor nodes also experience delays and excess energy consumption. Grid-based routing divides a network into grids that have common cluster heads. Sensor nodes in a particular grid send their data to their cluster head, which, in turn, relays data to another cluster head until it reaches the base station. However, for grids with a lot of sensor nodes, there can be a huge amount of data traffic causing quick energy depletion of the cluster head. Tree, chain, and grid-based routing indeed have the problems of long-distance communication and scalability. To overcome these shortcomings, routing approaches apply other clustering techniques. In cluster-based routing, the network is

subdivided into clusters with each cluster containing more than one sensor node with one designated as the cluster head. This method reduces bandwidth consumption, as fewer data packets are transmitted.

4. Techniques of Machine Learning in WSNs

ML has become very essential in solving various challenges imposed by WSNs. Broadly, these can be classified under supervised, unsupervised, semi-supervised, reinforcement, and evolutionary computation. Different approaches provide solutions to problems such as data aggregation, fault detection, localization, as well as energy optimization in WSNs (El Khediri, 2022).

4.1 Supervised learning

Supervised learning in WSNs is thus essential, as it uses labelled datasets to classify and predict data for applications in such areas as data aggregation, anomaly detection, localization, and routing. The DT, which is an example of a rule-based classifier using if-then rules, is employed for data aggregation, anomaly detection, and connection optimization, including routing optimization for mobile sinks in an energy-efficient way. Regression models in WSNs include linear regression, which is used for predicting continuous values in optimizing connection, resource allocation, and energy consumption. In spite of the computational demands, artificial neural networks (ANNs) remain very much in use for routing, fault detection, and localization, as they are very good at processing non-linear data. An ensemble technique called Random Forest (RF) improves accuracy and decreases overfitting, which makes it appropriate for anomaly detection and data transmission security. Support Vector Machines (SVM) are used for fault detection, localisation, and congestion management, including the detection of routing assaults, and they are effective at classifying high-dimensional data (Chen et al., 2018). A subset of artificial neural networks (ANN), deep learning (DL) is used for energy harvesting, routing, and data quality assessment. It improves anomaly detection and energy optimisation in large-scale networks by extracting high-level characteristics. Although its effectiveness varies with dataset size, K-Nearest Neighbours (KNN) classifies data based on neighbouring points and is used for data

Classifier data aggregation further reduces the amount of data transmitted to the base station, conserving energy with lesser-distance transmission. (Chan et al., 2020).

aggregation and defect detection. A binary logistic regression-based intrusion detection system (IDS) to detect selective forward and blackhole attacks with high accuracy but significant overhead, while combined regression and Q-learning to optimise WSN duty cycles, improving energy efficiency and throughput. Improved packet error rates without addressing energy and latency issues by using random forests to identify interference in IoT-based WSNs. Huang et al. (2021) used decision trees to anticipate forest fires. Coal mine safety monitoring and by Lu et al. (2021) for intrusion detection using ANN-based techniques. While Soomro and Jilani (2020) improved 3D localisation in 5G-IoT networks, deep learning approaches, Batiha et al. (2020), improved secure WSN middleware and smart agricultural monitoring, respectively. Alshinina and Elleithy (2018) enhanced fault identification accuracy using SVM-based techniques. Guo et al. (2018) improved K-NN for 3D sensor networks, addressing search efficiency in spite of processing and memory issues (Banihashemian et al., 2018). When combined, these supervised learning strategies greatly improve WSNs' usefulness, security, and efficiency for a variety of applications. Fig 2 shows the schematic diagram of the Supervised learning

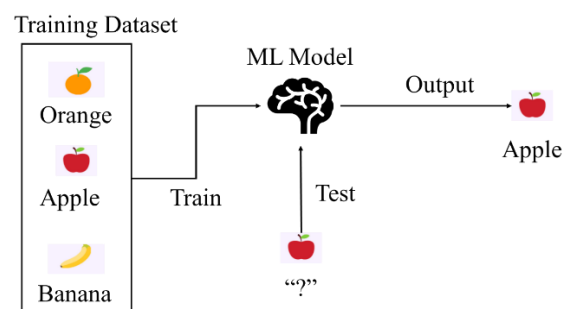


Figure 2. Supervised learning structure

4.2 Unsupervised learning

In WSNs, clustering, anomaly detection, and dimension reduction in unsupervised learning techniques are applied for energy optimization, data aggregation, and network efficiency. For example, k-means clustering is a method that operates based

on similarity metrics for data aggregation and energy optimization, although the cluster center choice can affect the method. Dao et al. (2020) implemented k-means clustering in their iMouse system to categorize monitored sites into clusters for continuous surveillance by mobile sensors, which are susceptible to outliers. In hierarchical clustering, the tree structure is employed for mobile sink path selection and synchronization. Likewise, Botao et al. (2020) applied hierarchical clustering with fuzzy c-means-based routing for boosting energy efficiency through a fitness function. Fuzzy c-means clustering, where data points can belong to several clusters, has also been applied in smart grid work-sleep strategies for better energy efficiency. Principal component analysis (PCA) is an unsupervised method for dimensionality reduction and fault detection; it was the technique used by Investopedia to delete low-variance components at cluster heads, but on the downside, it raised questions regarding energy efficiency and computing concerns. These approaches demonstrate that in many applications, unsupervised learning proves to be an operational concept for improving the performance of WSN.

4.3. Semi-supervised Learning

Semi-supervised learning is aimed at improving model accuracy by making use of both labeled and unlabeled data and is particularly useful in Wireless Sensor Networks (WSNs) for fault detection and localization, among other applications. For instance, semi-supervised models have been implemented to detect anomalies in sparsely labeled datasets thereby establishing their worthiness in situations where truly labeled data is limited. In the field of localization, (Dao et al., 2020) proposed in the past a semi-supervised learning technique that sustainably adapts to the changes in the environment or in the addition of newly added sensors on the algorithms, achieving high accuracy even in the cases of very less labeled data under mobile WSNs. Botao et al., 2020 added to this development by presenting a semi-supervised

learning algorithm that integrates large volumes of unlabeled data with small quantities of labeled data from network signals and physical spaces to improve localization accuracy. Through memory-consumption-supported semi-supervised learning with support vector regression, depending on the small-sized labeled dataset for the initial training, followed by regression for precise target localization, adds to this research domain. All these techniques together reveal a promising and flexible endeavor of semi-supervised learning into the WSN challenges, especially in resource-constrained settings (Investopedia, 2021).

4.4. Reinforcement Learning

A Q-learning based approach towards energy-efficient routing such that optimal paths are selected on the basis of data aggregation, residual energy, distance, and hop count, thus leading to increased network lifetime. The proposed approach DADF, namely Delay-Aware Data Fusion, is based on reinforcement learning techniques which balances delay and energy consumption for achieving a solution that surpassed the previous techniques in terms of throughput, energy efficiency, and end-to-end delay: Slotted ALOHA with Q-learning. RL-based Dynamic Power Management (DPM) in a multi-camera traffic monitoring system, by using a model-free learning algorithm and an online multi-layer artificial neural network (MLANN) for workload estimation to enhance decision making at dynamic workloads. RL in MANETs and WSNs is extensively used for all distributed activities, such as scheduling, service positioning, and routing as well as medium access control. Fig 3. shows the RL learning schematic diagram.

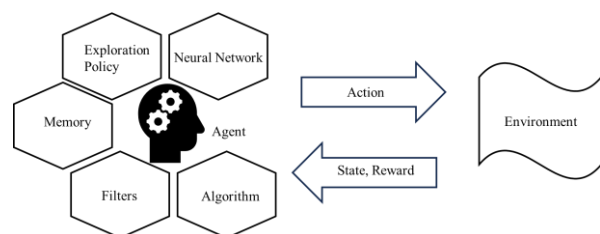


Figure 3. RL learning schematic diagram

agriculture, health, manufacturing, and transportation today, the gamut of applications involves IoT, cloud computing, mobile computing, and AI. It is the application of AI that is helping use

5. Emerging Technologies Used with AI in WSNs

With advancing technologies, the very ecosystem of human interaction and task execution is altered. In

WSNs in the improvement of healthcare, saving lives, using diagnostics to cure ailments, and increasing longevity. In education, virtual learning has supported accessibility, while blockchain serves to improve public services and bureaucratic processes. AI, 5G, IoT, blockchain, serverless computing, biometrics, NLP, AR, VR, robotics, and quantum computing a pool of emerging technology that may apply different innovative applications in WSNs. Fig 4. Shows the 4 stages of the IoT Solution Architecture.

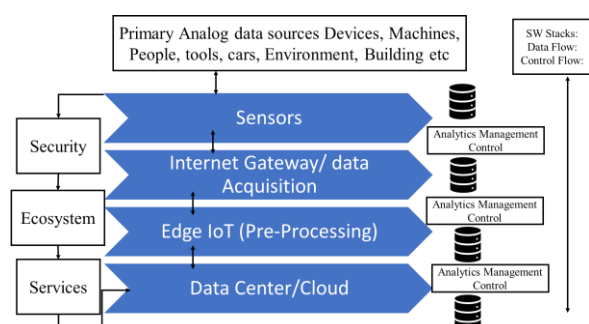


Figure 4. The 4 Stage of IoT solution Architecture

5.1. From IoT to AIoT

IoT, encompassing billions of connected devices, enables data collection and sharing. Initially applied in RFID tracking, IoT-generated data is expected to reach 73.1 ZB. AI combined with IoT forms AIoT, enabling intelligent decision-making without human intervention (Woldaregay et al., 2019). AIoT facilitates real-time data analysis, improving efficiency and trust in technology.

5.2. Cloud Computing

Cloud computing currently offers the availability of common resource through immediate service

6. Fog computing

Fog computing has been extensively studied across various years, addressing its definition, applications, security concerns, and future potential. (Yi et al., 2015) explored fog computing's definition, challenges, and SDN/NFV integration. (Stojmenovic et al., 2016) analyzed real-time applications and security vulnerabilities. (Alli & Alam, 2020) examined IoT-Fog-Cloud environments, emphasizing AI/ML integration. Mukherjee (2018) summarized resource allocation, research challenges, and applications. Mouradian

delivery. This includes the three services, namely Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). Of course, in AI, cloud computing enhances applications of Wireless Sensor Networks to unprecedented heights through the storage and analysis of large data sets (Investopedia, 2021). The variation made by AI will humanize the user interface, with remote control of devices being thereunder possible. Fig. 5 illustrates the Cloud computing architecture.

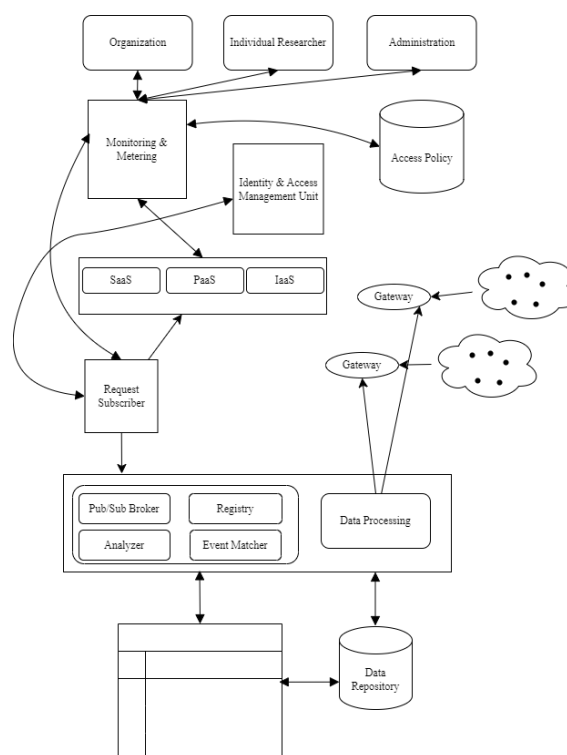


Figure 5. Cloud computing architecture

(2018) assessed fog advancements, architectures, and research directions. Yousef (2019) compared fog with other paradigms and categorized related research. Nadeem (2016) highlighted fog's exposure to security risks due to edge deployment. Singh (2021) categorized recent studies and emphasized architectural design challenges. Our paper reviews cloud computing paradigms preceding fog computing, proposes a taxonomy of security, operational, and data management challenges, and highlights privacy, communication, and application issues as key scholarly concerns.

7. Integration with 5G/6G networks for ultra-low latency and high reliability

The 6G wireless communication network (WCN) aims to transform global connectivity with intelligent, seamless coverage and reduced energy consumption. Targeting data rates up to 1 Tbps, latency one-tenth of 5G, 50x faster speeds, and 2x improvements in energy and spectrum efficiency (Hong et al., 2022), 6G is projected to handle over 5 zettabytes of monthly mobile data by 2030, alongside enhanced reliability, new spectrum use, and green communication. Initiatives like 6Genesis focus on ultra-low latency ($<0.1\text{ms}$ user plane, $<1\text{ms}$ control plane), spectral efficiency (>100 bps/Hz), sub-terahertz/terahertz operations, and battery-free IoT devices, supported by integrated satellite-terrestrial systems (Kuklinski et al., 2021). 6G will introduce native intelligence, enabling cognitive decision-making and global coverage (Hu et al., 2022), while powering advanced applications like AR/VR, healthcare IoT, autonomous vehicles, and smart IoT, driving large-scale technological innovation.

Conventional research focused on the solely working Intelligent Reflecting Surface (IRS), while recent studies emphasize multi-IRS coordination (Mei et al., 2022). Various optimization schemes based on CSI, including compressed sensing using Khatri-Rao and Kronecker products, two-stage channel estimation via angle differences and propagation path gains (He et al., 2021), Bilinear Adaptive Vector Approximate Message Passing (BAdVAMP) algorithm (Mirza & Ali, 2021), machine learning-based CSI estimation and subspace CSI estimation techniques (Wei et al., 2021), have been developed. Other methods involve message-passing algorithms for sparse matrix factorization (Liu et al., 2020) and tensor completion for estimating angles of arrival and path gains (Lin et al., 2021). CSI is essential for multi-IRS deployment (Ren et al., 2023), but the curse of dimensionality presents challenges, leading to blind beamforming techniques that optimize phase shifts without CSI requirements. Generalized blind beamforming for multiple IRSs has been proposed, estimating user terminal received power to deduce

phase shifts (Xu et al., 2024). CSI management becomes complex as the number of IRSs increases, though it is feasible in simpler scenarios (You et al., 2021). Two-time scale optimization (Zhao et al., 2021) and deep learning (Zhang et al., 2023) have been incorporated to reduce CSI estimation overheads. Due to network protocol and hardware limitations, CSI estimation remains impractical for existing IRS prototypes (Pei et al., 2021). A communication model based on inhomogeneous surface impedance boundaries has been formulated, optimizing reactive impedance boundaries (Di Renzo et al., 2022). RIS consists of reconfigurable elements creating phase shifts and amplitude adjustments, categorized into waveguide, refracting, and reflecting RIS (Liu et al., 2021). Optimization techniques for RIS-based wireless networks include transmission design (Pan et al., 2022). RIS enhances Integrated Sensing and Communication (ISAC), improving beamforming, signal coverage, and quality of service (Qian et al., 2021). Radar-based RIS deployments improve sensing performance (Aubry et al., 2021), while joint active-passive beamforming benefits rich scattering environments (Wang et al., 2022). Self-sensing RIS improves angle estimation accuracy (Shao et al., 2022), aiding in GPS-based localization (Elzanaty et al., 2021), signal strength-based localization (Zhang et al., 2021), and angle-of-departure/time-of-arrival methods (Björnson et al., 2022). Joint RIS beamforming has been implemented using alternating optimization, semi-definite relaxation, and Riemannian gradient techniques (Luo et al., 2022). A phase shift-based optimization scheme for multi-cell RIS-integrated multi-user MIMO systems employs linear mean square error methods and channel covariance matrices to maximize power gains (Gunasinghe & Baduge, 2023). RIS integrated with millimeter-wave and non-orthogonal multiple access optimizes energy efficiency through beamforming, power control, and user rate constraints (Yu et al., 2022). RIS-assisted ambient backscatter communication networks enhance energy and spectral efficiency, with evaluations based on symbol error rate, outage probability, and diversity order validated via Monte Carlo simulations (Le et al., 2024).

VLC technology is integrated with UAVs to enhance services like lighting and seamless communication, proving valuable for rescue and search operations. VLC-enabled UAVs improve energy efficiency using LED-based transmitters, reducing additional hardware requirements. This integration has gained research attention for optimizing communication networks, with UAV-based VLC location optimization maximizing network sum rate (Eltokhey et al., 2022). Joint optimization of power allocation, location, and user association has been studied in UAV-based VLC networks, while RIS integration further minimizes transmit power and increases energy efficiency (Cang et al., 2023). Multiple UAVs in VLC networks enhance optimization (Abdel-Rahman et al., 2023), and multi-agent reinforcement learning helps minimize transmit power and maximize sum rate (Maleki et al., 2022). Coverage probability improvements boost single UAV-based VLC networks (Anwar et al., 2022), with Particle Swarm Optimization (PSO) optimizing UAV trajectories based on user location, considering rate fairness, sum rate, and power consumption (Ibraiwish et al., 2024). Transmission Matrix-Assisted Neural Network (TMANN) reduces computational complexity by 59.23% while achieving a transmission rate of 6.689Gbps (Shi et al., 2024). Hybrid Li-Fi and Wi-Fi networks are explored (Ji et al., 2023), using an adaptive target condition neural network for load balancing, selecting access points based on user conditions. VLC integration with

8. Energy harvesting techniques for sustainable WSNs.

WSNs have emerged and grown into a fabulous technology incorporated in different application areas, from environmental monitoring to industrial automation (Ullo & Sinha, 2020). Only through highly effective power sources would these WSNs function for a long time. This is where the concepts of energy harvesting come into play, highly featured as the solutions to the problems of longer autonomy and green technology. These concepts, which include solar, thermal, mechanical, and electromagnetic energy harvesting technologies, are explored in this work along with their innovations and challenges (Singh et al., 2021). Recently, the developments in energy sources and their powers in

vehicular networks provides alternatives but faces challenges like fluctuations, mobility, and connectivity (Céspedes et al., 2023). Blind interference alignment VVLC, incorporating reconfigurable photodetectors, ensures channel response with linear independence. MIMO integration with VVLC enhances performance using a weighted two-step approximation methodology to improve SINR distribution and ergodic capacity (An et al., 2024). ACO-OFDM enhances spectral and energy efficiency through optimal power allocation, maintaining minimal mean squared error (Ma et al., 2022). Multi-band Carrierless Amplitude (m-CAP) modulation, considering received signal strength, enables VLC communication and sensing from the same signal (Shi et al., 2023). VLC links are evaluated for high-speed vehicles like trains, using relay-based networks with backhaul RF links between BS and relay and VLC links for UEs, assessing outage probability and bit error rate (Singh et al., 2023). For indoor flying VLC networks, an end-to-end learning framework optimizes the physical layer waveform, while mixed carrier communication integrates multiple streams for dimming and localization, analyzed using symbol error rate and SNR (Ahmad et al., 2024). Future WCNs integrate free-space optics, fiber wireless, and VLC to meet network demands, with VLC using m-QAM at 550MHz and a 39GHz mmWave operating link (de Souza Lopes et al., 2023).

extractions led to systems' increased battery lifespan and, in some cases, battery-free operations, thus lowering costs and environmental impacts Alioto, 2021). With the field of WSNs being so rapidly developing and an even faster increasing interest in the aspect of sustainability, this systematic literature review shall also serve in terms of pooling knowledge already existed and directing future developments toward higher efficiencies in energy harvest systems. However, even if there have been several studies done regarding energy harvesting techniques for WSNs, comprehensive reviews that systematically organize and synthesize these findings are still lacking. Filling this gap is the purpose of this study, which identifies, classifies, and characterizes the heterogeneous approaches in

the field of energy harvesting WSNs (EH-WSNs) within its ordered framework for future research.

8.1 Light and Heat

The operation of machines, particularly industrial ones, dissipates unused energy in various forms, including light, heat, mechanical vibrations, acoustic noise, and electromagnetic fields. Additionally, Heating, Ventilation, and Air Conditioning (HVAC) systems in buildings, geothermal activity, solar thermal energy, and body heat can be harnessed to power WSNs [130]. Despite its potential, thermal energy harvesting faces challenges such as low efficiency of Thermoelectric Generators (TEGs), the requirement for significant temperature differences, complexity and cost of integration into existing infrastructure, and miniaturization and durability concerns for WSN nodes. TEGs using the Seebeck effect are the primary focus of research in heat-to-electricity conversion, while photovoltaic (PV) cells are the predominant transducers for light energy harvesting, both utilizing PN junction semiconductors (Kim et al., 2023) (Xiao et al., 2023). Research in this field follows three main directions: identifying and amplifying energy sources, enhancing transducer efficiency, and improving circuit efficiency to minimize losses. Hybrid systems combining different energy sources have been explored, with TEGs integrated into solar panels to mitigate heat losses (Lineykin et al., 2021). Studies have also investigated harnessing industrial and solar heat, including industrial waste heat powering TEG modules (de Oliveira et al., 2023), sunlight concentrators for TEGs (Fang et al., 2023), and miniaturized TEG devices (Shen et al., 2021). Additionally, HVAC-induced temperature differences can be harvested using embedded TEGs (Lin et al., 2022), and Phase Change Materials (PCMs) help stabilize temperature gradients (Fang et al., 2023). The thermal resonator concept further improves thermal gradient maintenance, while Radioisotope Thermoelectric Generators (RTGs) utilizing nuclear elements have been explored for various environments analyzing PV panel efficiencies and optimizing power management (Gupta et al., 2023). Due to the inefficiency of silicon-based PV cells in indoor conditions, alternative materials such as perovskite cells (Olzhabay et al., 2021) and organic photovoltaic

(OPV) cells have been investigated, including environmentally friendly OPV modules (Zhang et al., 2022).

8.2. Electromagnetic, from power lines to radio waves

Electromagnetic fields from power cables can be harvested using coils. Maharjan et al., 2018 used C-shaped ferrites with copper coils to extract energy from domestic power wires. Rectennas, composed of an antenna and rectifier, convert RF waves into electricity (Benkalfate et al., 2022; Patil et al., 2023; Ullah et al., 2023). Benkalfate et al., 2022 created a meander line antenna for GSM 1.8 GHz, UMTS 2.1 GHz, and LTE 2.66 GHz. Patil et al., 2023 introduced 3D-printed concentric loops for 2.4 and 5.2 GHz. Song et al., 2021 proposed a broadband rectenna array for 1.7–2.7 GHz. Ullah et al., 2023 developed a metamaterial unit cell for 3.2 GHz and 5.4 GHz. Aboualalaa et al., 2023 integrated a voltage doubler rectifier with a stacked four-layer antenna (1.86–6 GHz). Many rectenna studies focus on the 2.4 GHz band. Liu et al., 2023 integrated antennas, rectifiers, and energy management circuits on PCBs. Rajawat and Singhal, 2020 simulated microstrip patch antennas for LTE bands at 850 and 900 MHz, while Verma and Sharma, 2022 designed an energy flow control circuit. Miller et al., 2020 and Wagih and Beeby, 2022 worked on 920 MHz band rectennas, incorporating Yagi and folded dipole antenna arrays, respectively.

8.3 Mechanical

Unlike classic thermomechanical or renewable energy wind or water systems for electrical generation that generate circular movement from flows, EH-WSN systems harness residual mechanical energy from flows, movements, and vibrations, exploiting nonlinear phenomena like mechanical resonance, nonlinear stiffness, and nonlinear damping to enhance energy transduction (Wang et al., 2023). Designing such devices involves material selection, structural design, and excitation mechanisms while mitigating undesirable nonlinear effects like frequency detuning and amplitude saturation (Dziadek et al., 2022). Mechanical energy sources include machinery, human movement, air, and water flows, where vibrations and acoustic noise—typically wasted—are harvested using

mechanisms like cantilevers with piezoelectric transducers tuned to resonance, applied in electric motors, railway systems, road vibrations, bridges, train bogie suspensions, agricultural machinery, and low-frequency wind turbine oscillations (McCullagh et al., 2014; Shan et al., 2023; Liu et al., 2023; Castellano-Aldave et al., 2023). Sea waves and wind/water flows, traditionally harnessed using turbines, are now utilized through vortex-induced vibration, flutter, buffeting, and galloping, requiring adaptive designs for omnidirectional wave motion (Zhang et al., 2021). Hybrid energy harvesting integrates multiple transducers, as seen in systems combining wind and sound energy (Izhar & Khan, 2023; Ahmad et al., 2023) and in electret-based triboelectric generators (Kan et al., 2021). These advancements highlight the growing focus on optimizing nonlinear dynamics and hybrid systems for improved efficiency.

Many studies on energy harvesting in wireless sensor networks (WSNs) have been validated only in simulations or laboratory conditions (Shen et al., 2023; Raja et al., 2023). (Hu et al., 2022) presented an origami assembly for flexible layer separation. Research has explored new triboelectric (Singh et al., 2023) and piezoelectric materials (Shan et al., 2023). Cantilever-based piezoelectric designs capture vibrations using an inertial element (Gibus et al., 2020). (Li et al., 2019) designed a multi-branched cantilever with tip masses tuned to different frequencies. (Alnoor et al., 2023) developed a TENG device with dual AC/DC output for vertical motion energy harvesting. Buckling beam structures, such as those by (Cao et al., 2022), enhance performance by incorporating inertial masses. Electromagnetic harvesters replace mass tips with oscillating permanent magnets near coils (Rubes et al., 2021). (Liu et al., 2023) introduced suspended permanent magnet systems, while (Wu et al., 2023) designed metal serpentine hinge suspensions with layered coils and alternate magnet positions.

9. SDN

Software-Defined Networking (SDN) is a paradigm in communications networks that separates the

8.4 The power management system (PMS)

PMS in HE-WSN enables efficient harnessing of limited energy from variable sources, regulating duty cycles between active and low-power modes (Avila et al., 2024). Energy consumption involves mote subsystems, while energy provision includes capacitors for buffering and supercapacitors or batteries for higher density storage. PMS ensures energy accumulation during sleep phases and usage during active states, requiring an adaptive charging circuit to match the Maximum Power Point (MPP). Electrical models, such as those by Ávila et al. (Avila et al., 2024), require further study. A system harvesting electromagnetic energy from power cables, calculating sleep intervals for self-sustained operation, as seen in Refs. (Maharjan et al., 2018). Several works, including, Lo and Shu (2022), and Li et al. (2022), designed PMS using discrete elements. An MPPT circuit. Most PMS designs use commercial ICs, with LTC3588-1 (Linear Technology) being the most common (Rana et al., 2022; Raja et al., 2023) (Rubes et al., 2021; Luo et al., 2023; Zhuo et al., 2023), alongside LTC3105 (Gao et al., 2020), LTC3108 (Lin et al., 2022; de Oliveira et al., 2023; Wang et al., 2023), ADP5090 (Analog Devices), AEM10941 (E-Peas Semiconductors) (Sultania & Famaey, 2023), BQ25570 (Haroun et al., 2022), LM2575 (Texas Instruments) (Sharma et al., 2018), BQ25505 (Avlani et al., 2022). LTC3588 is designed for C-SC, while others also support Li-Po and Li-ion batteries. Yue et al. 2020 introduced a PMS using the LTC4071 lithium battery charger for SC, but its discharge threshold causes energy wastage, requiring a boost circuit (Lin et al., 2022). A solution with a BQ25570 harvester, LTC3225 supercapacitor charger, and LTC3106 dual-path DC-DC converter, allowing efficient charge transfer between a supercapacitor and a backup battery. PMS plays a crucial role in sustaining WSN harvesting systems by efficiently converting, storing, and managing energy, ensuring continuous node operation with fluctuating inputs through MPP adaptation, loss minimization, and energy-aware scheduling.

forwarding and control planes. A centralized controller configures nodes to spare them having to talk with each other for filling their tables. The three-layer SDN architecture defined by the Open

Networking Foundation (ONF) is represented in Fig. 6, made of infrastructure, control, and application levels. Infrastructure Layer: This layer is also most commonly referred to as the data, and the lowest layer comprises forwarding nodes such as switches, routers, and access points.

Control Layer: Controllers that oversee data paths via a southbound interface (SBI), usually protected (e.g., using TLS), are housed at this layer. The most widely used SBI is OpenFlow. Controllers set up data paths, calculate forwarding rules, and supervise the network. Additionally, they can interface with other controllers, engage with network applications, and collect data from forwarding parts.

Application Layer: This uppermost layer consists of network applications that specify rules, such as load balancing, routing, and filtering. To regulate data path behaviour, controllers convert these rules into SBI instructions. Applications use a northbound interface (NBI), which is often built into the controller as subroutines, to connect with controllers.

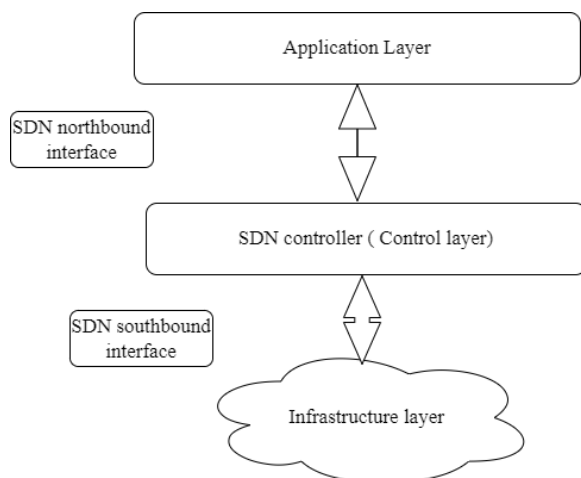


Figure 6. SDN architecture

Advances in WSN through SDN have led to various SDN-based approaches that improve different aspects of WSNs, classified into categories such as energy efficiency, routing, mobility, and reliability, as depicted in Figure 8. Energy efficiency remains a critical concern in WSNs, with sleep scheduling approaches helping to extend network lifetime by switching nodes into an idle state when their functionality is not required. The research on energy-efficient SDN-based WSNs can be classified into three areas: lifetime, coverage control, and

clustering. Prolonging network lifetime is essential, as computational tasks like path selection and neighbor discovery, along with data transmission, consume significant energy, with transmission alone accounting for approximately 80% of a node's power. Several SDN-based methods address this by utilizing energy-efficient node connectivity and a fuzzy logic-based algorithm that controls network topology to extend lifetime. Coverage control mechanisms, crucial for ensuring effective network monitoring, include target coverage for monitoring stationary or moving targets, area coverage for full network monitoring, and barrier coverage for intrusion prevention. SDN-based approaches for coverage control enable an SDN controller to schedule sensor nodes for target monitoring while minimizing energy consumption. Clustering enhances energy efficiency and routing performance by organizing nodes into groups led by cluster heads (CHs), which collect and forward data to the base station (BS). SDN-based clustering approaches include an SDN controller that gathers network topology data and installs rules for efficient data collection and an SDN-based clustering method that minimizes energy consumption by balancing communication costs and forming routing trees among clusters. Routing in WSNs aims to optimize congestion control, minimize delays, and maximize throughput, with SD-WSNs relying on SDN controllers to manage routing, reducing the computational burden on individual nodes, as explored in various protocols (Pantazis et al., 2013). Mobility in WSNs can be categorized as weak mobility, caused by network topology variations like node failures, and strong mobility, resulting from the physical movement of nodes due to external or intrinsic forces. An SDN-based mobility solution for barrier coverage in dynamic zones was proposed in, where a movement strategy controller determines new locations for nodes to ensure continuous monitoring. Reliability in WSNs is essential for maintaining the robustness of nodes, links, and controllers, as failures can lead to energy inefficiencies and data transmission issues. Strategies for improving reliability include the use of continuous-time Markov chains (CTMCs) for analyzing node reliability and deploying an additional SDN controller to prevent single points

of failure, ensuring reliable data transmission and network resilience in SD-WSNs.

10. Hybrid

5G technology is undergoing research and implementation to maximize its potential in high transfer rates, bandwidth, and low latency. While 4G enabled high-definition streaming, 5G is expected to revolutionize telecommunications by reducing latency to 1 ms in 2021, enabling applications like remote surgeries, intelligent traffic control, parking space monitoring, and real-time holographic communication. As 5G evolves, the role of LPWAN technologies, including Sigfox, NB-IoT, and LoRa, must be assessed for their adaptation to this interconnected era. Operating in the sub-gigahertz ISM band, these technologies offer high noise robustness and long-range communication at low data rates. Cities are key IoT markets, demanding real-time data in both urban and remote areas, requiring not only technical standardization but also social and governmental engagement, particularly in emerging smart cities. A critical urban challenge is traffic congestion, contributing to rising pollution levels. IoT applications leveraging LPWAN have been developed over the last five years to mitigate urban

interferences and optimize energy use. LoRaWAN has further enabled wireless positioning without GPS. Recent studies highlight the synergy of Machine Learning and IoT as a transformative force for urban applications. Urban sensor networks must consider factors like line-of-sight, coverage, and device lifespan. Various node-location strategies enhance connectivity, including predictive models for gateway placement and vehicular ad hoc networks (VANETs), which support dynamic node replacement and real-time data acquisition, often integrating cloud computing and high-resolution maps. Some algorithms, such as a latency and coverage-optimized data collection scheme, improve data efficiency using data mules, though LoRaWAN was excluded due to wireless transmission challenges. UAVs are increasingly utilized in such networks to extend coverage and optimize QoS. However, few studies provide experimental data on LPWAN deployment in large urban environments, leading to discrepancies between theoretical and real-world performance. Hybrid Wireless Sensor Networks (H-WSN), incorporating mobile nodes, remain underexplored despite their relevance for urban monitoring and emergency response applications. (Gopalakrishnan, 2014; Kim et al., 2020).

11. Role of IoT in WSN

Several research papers have explored energy-saving technologies in WSN and IoT-based systems. The study in designed a solar-powered precision agricultural network using IoT to provide real-time data on soil moisture, water levels, and temperature for smart agriculture. The work in examined IoT data gathering and decision-making concepts. Research in surveyed IoT-based WSNs for monitoring photovoltaic (PV) panels. The approach in improved energy efficiency in WSN-IoT environmental operations using the Chaotic Whale Optimization Process, showing better performance than traditional methods. A survey in analyzed delays, energy consumption, and packet

12. Applications of WSN

Because wireless sensor networks (WSNs) are affordable and simple to set up in a variety of settings, they are used in a wide range of applications. They are especially useful in hard-to-

delivery ratios in WSNs, improving AODV routing through protocol optimization. Given WSN-assisted IoT's energy limitations, proposed the EAMMH-RP protocol, balancing energy distribution among sensor nodes for efficient multi-hop communication. The protocol in introduced clustering and multipath strategies to minimize energy use and enhance reliability, tested in the Castalia simulator. Routing algorithms were reviewed in based on energy awareness, delay, and data transmission efficiency. Finally, optimized a conventional routing protocol, introducing an innovative system that bridged the gap between WSNs and real-world heterogeneous settings, with simulation results validating its improvements.

reach places, such isolated or submerged regions. As shown in Figure 7, WSN applications are divided into a number of important categories (Kavitha et al., 2024).

12.1 Applications in Healthcare

WSNs are essential in the healthcare sector because they keep an eye on critical indications including heart rate, blood pressure, and temperature. Real-time monitoring of these indicators is made possible by wearable technology in both exterior environments, like residences, and healthcare institutions, like hospitals. Wearable patient monitoring, home support systems, and hospital patient surveillance are the three primary categories into which WSN applications in healthcare fall. Specialised sensors are used in each region to guarantee precise and trustworthy data gathering.

12.2 Applications in the Environment

The role of WSN is that it facilitates the environment for monitoring, particularly for far and dangerous places where most of the observation occurs. Water quality, air quality, floods, earthquakes, and volcanoes monitor and record pollution above the ground along with emergency warning systems; environmental applications involve some of these. These applications incorporate WSN data efficient and rapid manipulation for environmental management and disaster relief.

12.3 Applications for Plants and Wildlife

Every country prioritises protecting its animals and plants. Within this field, WSNs are used in a number of subcategories, including as animal management, crop monitoring, and greenhouse monitoring. These applications support sustainable agriculture practices and biodiversity conservation by using certain sensor types to guarantee ideal circumstances for plant development and animal welfare.

13. Attack in WSN

Studies examining the different attack types and detection techniques across layers of WSNs have a long and rich history. Bengag et al. (2020) developed a detection technique based on network metrics such as packet delivery ratio (PDR) and energy consumption (ECA). Dell Valle Soto et al. (2021) [237] focused on low-energy segments and evaluated the detection on protocols like PEGASIS and LEACH. Da-Wen Huang et al. (2021)

12.4 Industrial Applications

Providing effective monitoring and management within an industrial environment, getting rid of many problems. Logistics, Robotics, and Machinery Health Monitoring are the three major applications in industries. These applications utilize WSN to deliver increased operational effectiveness, reduced downtime, and enhanced safety in industries.

12.5 Urban Uses

Thus a wide variety of sensing capabilities are offered by the WSNs and would prove to give very good information on urban surroundings both within and outside cities. Applications now in transportation systems, smart cities, smart homes, and structural health monitoring, have extensively used this technology. Thus capturing the different events over time and space, these WSN help in smarter, greener cities in the future.

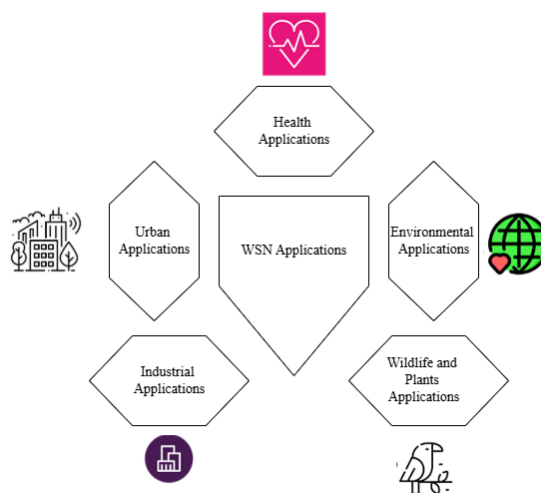


Figure 7. Applications of the WSN

introduced a hybrid algorithm for dynamic WSN, and Fotuhi et al. (2020) presented the ASDA-RSA method for denial of sleep attacks at the link layer. Hristozov et al. (2020) diminished these attacks through lightweight authentication. Clement Sunder et al. (2020) attempted the identification of blackhole attacks using AODV routing and machine learning techniques, respectively, while Mustafa et al. (2020) and Singh et al. (2020) rebuffed in-network misdirection attacks through reinforcement learning and cluster-head-free

algorithms. Selective forwarding attacks were dealt with by Singh et al. (2020) from the stance of ANN and PSO techniques. Sybil attacks have been studied by Jamshidi et al. (2019) and, while sinkhole attacks were investigated by Dhivya et al. (2021).

13.1 Limitations

Nevertheless, several limitations are still inherent in these studies. Bengag et al. (2020) had difficulties with reducing false alarms and improving detection rates concerning jamming attacks. Dell Valle Soto et al. (2021) indicated their dependency on packet loss and energy consumption, while Da-Wen Huang et al. (2021) called energy inefficiency in dynamic WSN. Fotohi et al. (2020) argued energy consumption must be reduced for network lifespan in denial of sleep attacks. Hristozov et al. (2020) validated the inability to detect other attack types apart from exhaustion attacks. Clement Sunder et al. (2020) pointed out that at the network layer, real-world sensor testing for black hole attacks was not present. Singh et al. (2020) noted energy consumption related to the misdirection and selective forwarding attacks. Tamilarasi et al. (2020) pinpointed accuracy limitations against wormhole attacks. Jamshidi et al. (2019) and Angappan et al. (2021), on the other hand, struggled to detect Sybil attacks with a smaller number of nodes. Finally, Prabakaran et al. (2020) stressed the urgency for faster detection and energy consumption in counter measures against DoS attack. All these limitations call for more investigations towards making WSN security mechanisms robust and efficient.

13.2 AI challenge

The AI has been impacting human life in the main part other than improving costs, efficiency, and productivity in various sectors such as manufacturing, healthcare, and other industries. In the case of WSNs, AI technologies promise to improve network intelligence and efficiency by enabling real-time monitoring, flexibility, and adaptive behavior. The integration of AI into WSNs brings with it many challenges: computing power, data privacy, knowledge management, and the biggest of them all - data scarcity. The high cost of routing is one of the major issues in case of an unforeseen situation when the AI techniques are used for self-configuration and adaption through

the use of learning algorithms; do so with verbalized non-committal replacement of the routing; the communication overhead thereby increases, leading to connectivity issues (Ijaz et al., 2020). Another challenge would be the communication costs of some ML techniques requiring multiple communication rounds for observation and learning, which would lead to higher costs and aggravating complexity, especially in systems using distributed methods like federated learning (Manman et al., 2021). These costs were supposed to be minimized through centralized approaches where storage and processing are handled using cloud systems. Another major concern is energy consumption, especially because the computational and communication resources demanded by AI techniques, particularly ML, require a balance between the optimum performance and optimization of the usage of resources (Fadlullah et al., 2018). Bayesian algorithms have recommended addressing absence of complete datasets and improving adaptability (Adel et al., 2020). Interoperability among sensors of different manufacturers with diverse communication protocols is still a major concern. Lastly, security and privacy issues rise because more intelligent systems collect more sensitive data, making them susceptible to cyber-attacks and raising privacy-related issues. These challenges are necessary for incorporating AI in WSN. Fig 8 depicts the challenges of AI in WSN.

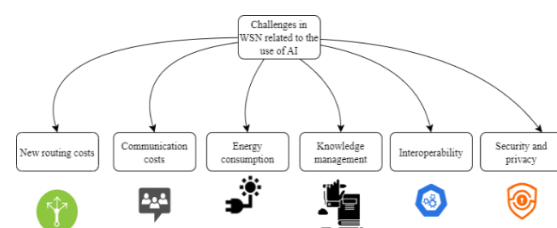


Figure 8. AI challenges in WSN.

Due to the extensive research in power saving, optimization, longer lifetime of wireless sensors is also often desired in intensive sensing applications, making power supply and reservation a serious challenge for implementing Wireless Structural Health Monitoring Systems (WSSN) over wired alternatives. Strategies like optimizing cluster size, employing low-power mode sensor nodes, and implementing energy harvesting have been

considered for this purpose. Moreover, adaptive methods to switch WSS into low power or deep-sleep modes, either rule-based or data-driven, appear feasible and could be effective in optimizing power consumption and lifetime of the sensors.

13.4 WSN challenge in IoT

The amalgamation of Wireless Sensor Networks (WSN) into the Internet of Things (IoT) involves a plethora of challenges owing to the heterogeneity of devices and the requirement for sound security mechanisms. Real-time management has a substantial bearing upon valid service gateway design and middleware that ensures minimal data transmission and real-time communication only in case of exceeding threshold limits. Security and privacy play a pivotal role on the agenda as connecting WSNs to the internet would leave them vulnerable to global attacks, demanding robust security frameworks that justify their limited computing power, energy, and memory constraints. Quality of Service (QoS) stands another challenging aspect to be rightly taken care of, as it directs heterogeneous IoT devices to share work efficiently; applications of the very current QoS techniques must be augmented to accommodate the dynamic nature of the networks. Configuration tasks related to network setup or self-healing are other nightmares, which require user intervention for overall smooth operations. Availability hence becomes one key issue as compromised nodes would disrupt the WSNs; hence, researchers strive to develop encryption algorithms and methodologies, guaranteeing continued operational availability. Data integrity must be assured so that malicious nodes could not inject false data or corrupt the transmission of truthful data, delivering true information. Confidentiality is equally required, where encryption algorithms like AES and Triple DES are used, but disabling some probable attacks that allow a traffic analysis or a group key compromise must be taken into consideration. Effectively countering all these challenges entails the successful deployment of WSNs in IoT applications.

13.5 Challenges in energy harvesting

According to the literature addressed in this text, the major tribulations faced by energy harvesting for

Wireless Sensor Networks (WSNs) may be characterized by the four most important factors: the variability and intermittency of energy resources, the greatly scarce amounts of energy regularly harvested, and the above two aspects lead to the need for an efficient arrangement of energy usage. Thus, the solutions to overcome the challenges require attention to three main areas: energy conversion efficiency, energy storage technologies, and energy management systems.

Most research in this area has practical and thus applies to engineering challenges that require solutions specifically tailored to the deployment environment and operational conditions. This consideration requires that energy sources be looked upon in an unpredictable light; therefore, it has to assess each WSN deployment scenario and operating regime separately. This guarantees that the sizing of energy harvesting and storage components is done appropriately, ensuring the network's proficiency in operation during times of energy-scarcity conditions. Future explorations may include the development of forecast models integrated with energy requirement analyses which will guide system sizing thereby allowing operation adaptability. The improvement in energy conversion efficiency and storage would offer new vistas in materials science and manufacturing technique. Additional discussion includes the study of approaches for energy conversion that cover multiple energy transformation pathways for increasing overall efficiency of systems. Furthermore, the energy bearing capacity encompasses alternatives such as the phase change material (PCM), which explores latent heat on phase transition for energy storage. This has received notable attention in the last few years, as reflected by the Scopus indices, and should thus be included in further investigations.

Since Energy Management can be further classified into two major components: Managing the power of the system, i.e., PMS, and Energy Consumption Optimization for Mote. PMS would, thus, include capabilities to create an environment surrounding it that enables it to be highly efficient even at lower levels of energy produced by transducers and would also maximize a well-stored energy use for the most part where energy harvesting is low. In comparison

with the other traditional methods of energy consumption, such as that which occurs in battery-powered sensor nodes, most power is consumed by the radio activity being performed in the motes. The consumption management then alters the duty cycle of radio, depending on the frequency of data update, network conditions, and protocol used for communication. Further, bibliometric approaches show ongoing research in routing protocols, network lifetime optimizing, and prediction models that inherently align with the historical interests of WSNs. Energy harvesting remains an area with widespread question queries, particularly on compatibility, interoperability, and scalability.

There is a summary of visual impacts that can be categorized as challenges in energy harvesting by WSNs as in figure 9. The conclusion is that this is highly complicated and requires research in materials science, nanotechnology, and electronics

14. Future trend

ML methods have significant influence on future developments in data aggregation and fusion techniques in WSNs. Among the commonly used methods in the literature are principal component analysis (PCA), singular value decomposition (SVD), artificial neural networks (ANN), denoising autoencoder (DAE) neural networks, Bayesian learning, and RL. They comprise all important aspects, such as defining aggregation mechanisms, aggregation node selection, and volume control for collected data. Therefore, besides the solutions proposed, there is a requirement for incorporating such different approaches into a single framework which is necessary for unified solutions that would minimize network traffic without compromising quality of data at the base station.

One of the major issues found in current research is that not enough attention has been paid to network mobility support. Specifically, it fails to address mobility in all dynamic wireless networks that may consist of one or more nodes being mobile. Absent such provisions, the system can end up being inefficient or at worse degrade in performance in such scenarios. An example is where conventional RL does not perform well in such heterogeneous

to lead to an improved efficient and sustainable system. Interdisciplinary collaboration and new research can pave new paths out of these woods and improve the technology's penetration for energy harvesting capabilities in various real-world applications.

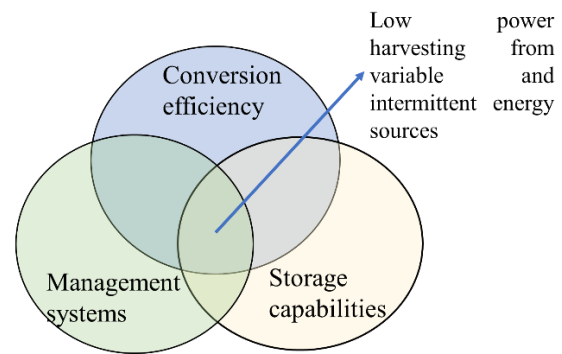


Figure 9. Challenges faced by energy-harvesting WSNs

conditions. To address this phenomena of dynamic wireless nonstationary, deep reinforcement learning (DRL) has been suggested. Their study recognizes that mobility should be taken into account while designing network architectures, which should not ignore low consumption of power.

Advancing into the future, overcoming the computational challenges in WSN would require bringing the focus more onto the IoT, edge and fog computing integration. As such, intelligent strategy design for load distribution and task planning for its execution in a fog node or edge with computation-intensive activities concerning ML, RL or DRL would be part of the solution required. Given this, the schemes ought to meet the deadline of applications while appropriately balancing workload among computing nodes in the IoT network and surrounding environment. This would go a long way in curtailing delays associated with processing in the cloud. In addition, energy efficiency at the edge must also receive high consideration with preference on lightweight algorithm development, which consumes less computation energy. All the above would go a long way into making WSNs scalable and sustainable in the near future.

15. Discussion/Summary of the Study

This comprehensive review highlights the evolution, challenges, and future directions of Wireless Sensor Networks (WSNs), emphasizing their integration with emerging technologies such as the Internet of Things (IoT), 5G/6G networks, machine learning (ML), and energy harvesting techniques. WSNs, initially developed for specific limited applications, have become a cornerstone of modern IoT systems, enabling applications in healthcare, environmental monitoring, industrial automation, and smart cities. However, their widespread adoption is hindered by several operational challenges, including energy constraints, limited processing and storage capabilities, and vulnerabilities in wireless communication.

15.1 Key Challenges and Solutions

15.1.1 Energy Efficiency

Limited energy supply is the critical challenge for nodes because these ones are often battery-powered with non-rechargeable batteries. The first solution to address this problem is energy harvesting methods such as solar energy harvesting, thermal energy harvesting, and mechanical energy harvesting. Power management systems and energy-efficient routing protocols are the other examples of techniques to prolong the lifetime of the entire network.

In addition, machine learning techniques shall prove useful, especially reinforcement learning (RL) and deep reinforcement learning (DRL), for energy optimization and betterment in energy-efficient networks.

15.1.2 Data Handling and Processing

Data aggregation, fault detection, and localization work with several difficulties related to limited computational and storage capacities of the sensor nodes. Several data processing and decision-making capabilities have been brought about in WSNs by employing supervised, unsupervised, and semi-supervised learning techniques.

The edge and fog computing modes of integration have come up for the offloading of computing-intensive tasks, which would otherwise have a

detrimental effect on latency while simultaneously improving real-time data processing capabilities.

15.1.3 Security and Privacy

WSNs are subjected to various attacks such as jamming, denial of sleep, blackhole, and Sybil. Research has been done to use machine learning-based intrusion detection systems and secure routing protocols to manage these security threats. However, some areas are yet to be improved: reducing false positives, improving the detection rate, and energy efficiency in security mechanisms.

15.1.4 Connectivity and Coverage

It is a tough task to maintain network connectivity while optimizing coverage because it deals with a dynamic environment comprising mobile nodes. Hierarchical and cluster-based routing protocols have been developed for coverage improvement as well as energy efficiency. A possible integration of Software-Defined Networking (SDN) was also explored into the entire picture to enhance its network management and reliability.

15.2 Integration with Emerging Technologies

15.2.1 IoT and AIoT:

Integration of WSN with IoT creates real-time data collection and analysis to make intelligent decisions for applications such as smart city and precision agriculture. The AI-IoT (Artificial Intelligence and The Internet of Things) is a concept in which the functioning of WSN is enhanced through autonomous systems that respond and adapt to dynamic environments.

15.2.2 5G/ 6G Networks

With respect to WSN applications, 5G and anticipated 6G lower latency, higher reliability, and better energy efficiency. The integration of WSN into such 5G/6G networks, therefore, constitutes the basis for innovative applications in remote surgery, autonomous vehicles, and real-time holographic communication.

15.2.3 Machine Learning and AI

The use of ML techniques (supervised, unsupervised, and reinforcement) aims to optimize WSN performance. The aforementioned techniques are used for data aggregation, fault

detection, localization, and energy optimization. Aspects like high computational complexity, data privacy issue, and interoperability need to be dealt with for effective integration.

15.2.4 Energy Harvesting and Sustainability

Different energy harvesting techniques such as solar, thermal, and mechanical energy harvesting have been put to examination to meet energy constraints for WSNs. This involves developing hybrid systems that combine multiple alternatives and advanced power management in order to attain energy-efficient and sustainable systems.

15.3 Future Directions

15.3.1 Mobility support

Future research should be conducted in the field of WSN architecture development for mobile nodes to achieve seamless connectivity and efficient data transmission in dynamic environments. Deep reinforcement learning (DRL) and other adaptive algorithms are what help in addressing the challenges introduced by network mobility.

15.3.2 Lightweight algorithms

16. Conclusion

The examination presents a wide spectrum of advancements, challenges, and upcoming directions in Wireless Sensors Network (WSN) studies with an eye toward merging them with the new technological paradigms like internet technology, 5G/6G networks, machine learning, and energy harvesting. The research extends the perception on how WSNs would potentially alter integrated diverse applications, including health, environment, and industrial applications, while discussing conspicuous challenges like energy efficiency, data processing, security, and connectivity hampering their effective performances. The optimization of WSN performance through real-time decision making and better energy management is reportedly promising when combined with AI and machine

Lightweight algorithms dedicated to data aggregation, fault discovery, and energy optimization result in reduced overhead that would otherwise be the case with centralized services in a sensor network. They would need to be light in weight functions as their behavior would be necessarily constrained resource-wise.

15.3.3 Interdisciplinary Collaborations:

Addressing the challenges in WSNs needs a cross-disciplinary approach, so that it should be dealt with according to materials sciences, nanotechnology, and electronics. Novel energy harvesting, storage, and management systems will be a must for developing sustainable and efficient WSNs.

15.3.4 Edge and fog integration:

Network data gathering can become hugely improved thanks to the emerging synergies that WSNs can have with edge and fog computing in terms of data processing and latency reduction. Future research should work toward intelligent development strategies for workload distribution and optimal allocation of computational tasks among edge and fog nodes.

learning techniques. Despite this revelation, several challenges remain, such as computational limitations, mobility support, and lightweight algorithms for increased scalability and sustainability. In future studies, efforts should majorly be directed toward the development of unified frameworks for data aggregation and fusion, IoT-Edge-Fog computing, and advanced energy harvesting and storage technologies. Non-stationarity will be another dynamic aspect of networks that will need new solutions through the deep reinforcement learning approach. Compatibility, interoperability, and scalability will need argumentation in energy harvesting solutions. By promoting interdisciplinary talent and innovative research methodologies in this field, the discipline may change the game and create new opportunities for WSNs in practical use.

5. References

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Conflict of Interest

The authors declare that they have no conflict of interest.

Competing Interests

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