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REVIEW

Wireless Sensor Networks in Renewable Energy Monitoring: A Comprehensive Survey of Protocols and Applications

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ABSTRACT

The global shift to sustainable energy has heightened the demand for smart, robust, and efficient monitoring systems. Wireless Sensor Networks (WSNs) play a key role by enabling real-time data collection, decentralized control, and flexible communication in renewable energy applications. This review presents a comprehensive analysis of WSN architectures, routing protocols, and deployment strategies tailored to photovoltaic (PV) arrays, wind energy systems, hydroelectric plants, and smart microgrids. Core operational challenges are examined through a critical evaluation of energy-aware routing protocols including LEACH, PEGASIS, TEEN, ZRP, and advanced variants like EE-OLEACH and PT-Hybrid. Real-world applications, such as offshore wind farms, rooftop PV installations, and smart grid in underserved regions, underscore the practical value of WSN-based monitoring. Emerging solutions such as AI-enhanced clustering, blockchain-secured data integrity, and federated learning for decentralized intelligence demonstrate the convergence of WSNs with next-generation technologies. Additionally, the integration of edge computing and future 6G frameworks is explored for ultra-reliable, low-latency communication. However, gaps remain in technological readiness, large-scale deployment validation, and the need for cross-layer protocol optimization. The review concludes that while WSNs are already central to modern renewable energy systems, ongoing innovations in energy harvesting, secure networking, and intelligent analytics will further elevate their role in creating autonomous, self-healing, and high-performance energy infrastructure.

Keywords: Wireless Sensor Networks (WSNs), Renewable energy monitoring, Energy-efficient routing protocols, Smart grid integration, Edge computing and AI optimization

1. Introduction

The global transition toward sustainable energy has driven the integration of intelligent monitoring systems into renewable energy infrastructures. Among these, Wireless Sensor Networks (WSNs) have emerged as a transformative technology, offering real-time environmental monitoring, adaptive control, and autonomous decision-making capabilities in solar and wind energy, and hydroelectric systems [1], to enhance operational efficiency and prolong system [2]. A WSN typically comprises spatially distributed sensor nodes capable of sensing, processing, and wirelessly communicating data, forming a collaborative framework to capture critical system metrics such as temperature, voltage, current, wind speed, and irradiance [3]. However, the deployment of WSNs in renewable energy scenarios presents critical challenges; particularly those linked to energy efficiency, network resilience, and protocol design [4]. Sensor nodes are often deployed in harsh, remote, or inaccessible environments, where battery

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replacement or maintenance is impractical. Therefore, advancing energy harvesting (EH) techniques is crucial for enhancing network longevity while maintaining reliable and high-quality data transmission in sustainable WSNs [5]. Recent studies have emphasized the importance of routing and medium access control (MAC) protocols [6], especially energy-aware designs, in reducing communication overheads and balancing energy loads within the network [7]. For instance, the use of clustering techniques (e.g., Low Energy Adaptive Clustering Hierarchy (LEACH) [8], Power-Efficient GAthering in Sensor Information Systems (PEGASIS), and bio-inspired algorithms has been shown to significantly enhance network lifetime through efficient cluster head (CH) selection and data aggregation mechanisms [9]. Simultaneously, advances in EH technologies have facilitated the development of self-sustaining WSNs that mitigate energy constraints and reduce operational costs [10]. Furthermore, the integration of WSNs into the broader Internet of Things (IoT) ecosystem, as seen in smart grids, microgrids, and decentralized power systems, enables dynamic energy management and predictive maintenance through machine learning (ML) [11], and edge computing frameworks [12]. Yet, despite significant progress, several technical gaps remain, including protocol adaptability to fluctuating environmental conditions, trade-offs between energy efficiency and communication reliability, and the lack of standardized performance benchmarks for renewable energy applications. Fig. 1 provides a high-level overview of the structure and key domains of WSNs as applied to renewable energy systems. It visually organizes WSN components, communication protocols, and application sectors such as solar [13], wind [14], and hydropower systems [15], setting the stage for deeper discussion in the subsequent sections. This review aims to provide a comprehensive overview of WSN protocols and applications tailored for renewable energy monitoring. Emphasis is placed on routing strategies, energy-aware designs, and real-world implementations, with critical evaluation of their effectiveness, limitations, and suitability in next-generation smart energy systems.

2. Fundamentals of WSNs

WSNs form a foundational layer in the architecture of intelligent monitoring systems [16]. They consist of spatially distributed sensor nodes that cooperatively sense, process, and communicate environmental or system data to a centralized or distributed sink for further analysis or control [17]. Their relevance in renewable energy monitoring arises from their ability to perform real-time, autonomous, and cost-effective data acquisition in geographically dispersed and harsh environments [18].

2.1. General architecture (sensor nodes, gateway, sink)

A typical WSN is composed of the following core components.

2.1.1. Sensor nodes

Wireless sensor nodes in intelligent buildings are essential for monitoring environmental parameters like temperature, vibration, and irradiance [19]. Traditionally powered by batteries, these nodes face limitations due to frequent maintenance and environmental impact [20]. In case of EH technologies into wireless sensor nodes significantly enhances the efficiency and sustainability of intelligent building systems [21]. As noted by Minoli et al. (2017), these sensor nodes enable the seamless deployment of intelligent building control networks without the need for traditional electrical wiring; both for data communication and power supply [22]. This is particularly beneficial in retrofitting existing infrastructure or installing sensors in hard-to-reach areas, where wired installations are labor-intensive and costly [23]. EH devices like piezoelectric, thermoelectric, and light-based harvesters can supply power to sensor nodes, either partially or fully, reducing dependence on batteries. Building systems like HVAC, lighting, and water pipelines offer ideal sites for harvesting energy as shown in Fig. 2 [24]. By integrating EHs, buildings can deploy more autonomous, low-maintenance, and sustainable WSNs, aligning with smart energy goals and reducing carbon emissions. The sensed data is converted into electrical signals, processed locally via a microcontroller, and transmitted wirelessly through RF modules to a gateway or base station (BS). This design allows for highly flexible and distributed monitoring architectures. By utilizing EH, WSN nodes can be deployed in inaccessible or maintenance-sensitive areas without concerns about frequent battery replacement [25]. This supports Minoli's argument regarding reduced reliance on wiring and external power sources. Moreover, WSNs can be easily configured, scaled, and reprogrammed at minimal cost, as Huang and Mao (2017) highlighted [26]. Their inherent modularity and wireless communication capabilities allow for rapid integration with existing building systems. As building complexity increases and real-time energy optimization becomes crucial, the role of dense WSN deployments becomes even more critical [27]. While WSNs have historically faced challenges related to signal strength and data

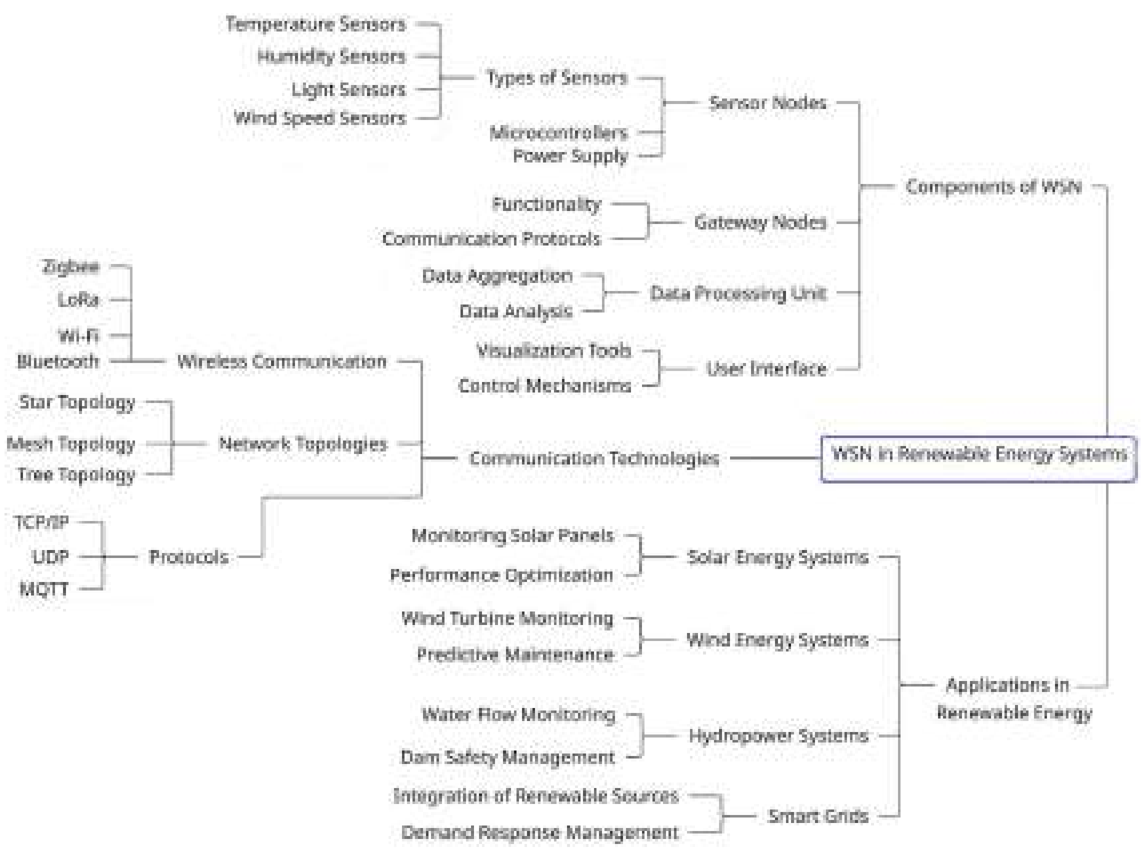

Fig. 1. The major components, communication technologies, and application domains of WSN in renewable energy systems.

congestion, the emergence of ultra-dense wireless architectures and low-power wide-area networking technologies (LPWANs) is helping to overcome these issues, as noted by Can and Sahingoz (2015) [28].

2.1.2. Gateway or CHs

In many hierarchical WSN topologies, certain nodes are designated as CHs. These nodes aggregate data from nearby sensor nodes and forward it to the sink node. They are often more resource-rich in terms of energy and computational capabilities and play a critical role in optimizing data flow and reducing communication overhead [29]. Rahul and Kaarthick (2023) introduced advanced algorithms; Node Quality-based Clustering Algorithm using Fuzzy-Fruit Fly Optimization (NQCAFFFOCHGS) and its fault-tolerant version; that improve CH and gateway selection in WSNs. These methods use fuzzy logic and learning automata for adaptive clustering and include a self-healing mechanism to restore network connectivity in case of node failures, enhancing reliability and extending network lifetime [30]. Additionally, strategies like the Cluster Chain Weight Metrics (CCWM) approach focus on balancing load and energy consumption across the network by assigning weights to key service parameters such as node energy, connectivity, and transmission cost [31]. This leads to more efficient CH selection and the formation of balanced clusters. As demonstrated by Mahajan et al. (2014), CCWM strategy improved overall network performance by significantly extending network lifetime; outperforming conventional protocols like LEACH, WCA, and IWCA by 51%, 27%, and 18.8%, respectively [32]. Gateway placement strategies, such as Intra Cluster Gateway Optimization using Particle Swarm Optimization and Genetic Algorithms (ICGW-PSOGA), also help in minimizing intra-cluster communication distances and ensure optimal sink placement to extend the network lifetime as recorded by Raghavendra & Mahadevaswamy, 2021 [33]. Further developments have been carried out by Jibreel et al. in 2022 in heterogeneous gateway-based multi-hop routing protocols, such as Heterogeneous Gateway-Based Energy-Aware Multi-Hop Routing (HMGEAR), provide enhanced data delivery performance and energy balancing by integrating energy-aware metrics with multi-hop strategies and energy hole mitigation techniques [34]. Artificial intelligent (AI) enabled approaches, like modified density-based clustering and fuzzy logic-assisted

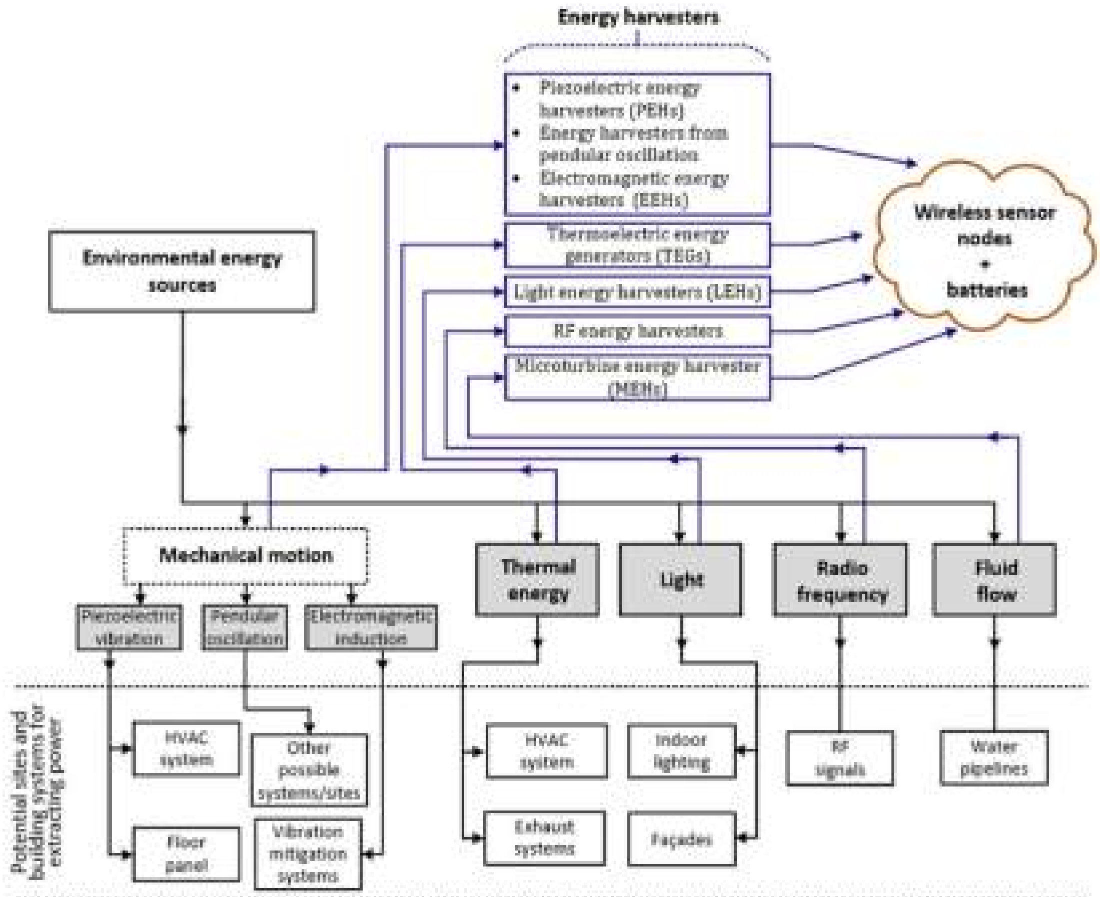

Fig. 2. Diagram of some ambient energy sources in buildings with their respective energy harvesters used to supply power to sensor nodes within WSNs.

routing, are also gaining traction, offering increased cluster head longevity, reduced latency, and improved data throughput, especially in dynamic and mobile environments like Aeronautical Ad Hoc Networks as recorded by Shahbazi et al., 2023 [35].

2.1.3. Sink node or BS

This is the endpoint that collects all sensor data, often connected to a central server, cloud system, or Supervisory Control and Data Acquisition (SCADA) platform [36]. The sink processes or forwards data for further computation, visualization, or control action. In renewable energy systems, the sink is typically positioned at the control center of a solar farm or wind station [37]. Advanced industrial-grade sink nodes [38], such as the industrial wireless BS platform described by Daniel et al. (2011), offer enhanced processing power, communication flexibility, and robust environmental protection (IP) [39]. For example, they have achieved IP65 rating and operation from –40 to +85°C, making the industrial-grade sink nodes ideal for deployment in harsh, outdoor energy environments. These BSs enable centralized data processing and significantly reduce the computational burden on individual sensor nodes, which are typically low-power and resource-constrained [40]. Moreover, the integration of WSNs with SCADA systems extends monitoring capabilities through a multi-hop architecture, offering redundancy, scalability, and fault tolerance. As shown by Grilo et al. (2014), such integration enhances real-time visibility and remote accessibility through web-based interfaces [41]. Simultaneously, cluster-based data aggregation techniques like SCADA, as proposed by Jain et al. (2022), further optimize network lifetime and energy efficiency by reducing redundant transmissions and dynamically rotating CHs and relays based on topology and energy metrics [42].

This modular architecture allows for scalable deployments and supports diverse applications, including environmental monitoring, solar panel diagnostics, wind turbine condition monitoring, and smart grid integration. Fig. 3, Illustration of a typical WSN architecture including sensor nodes, gateways, and

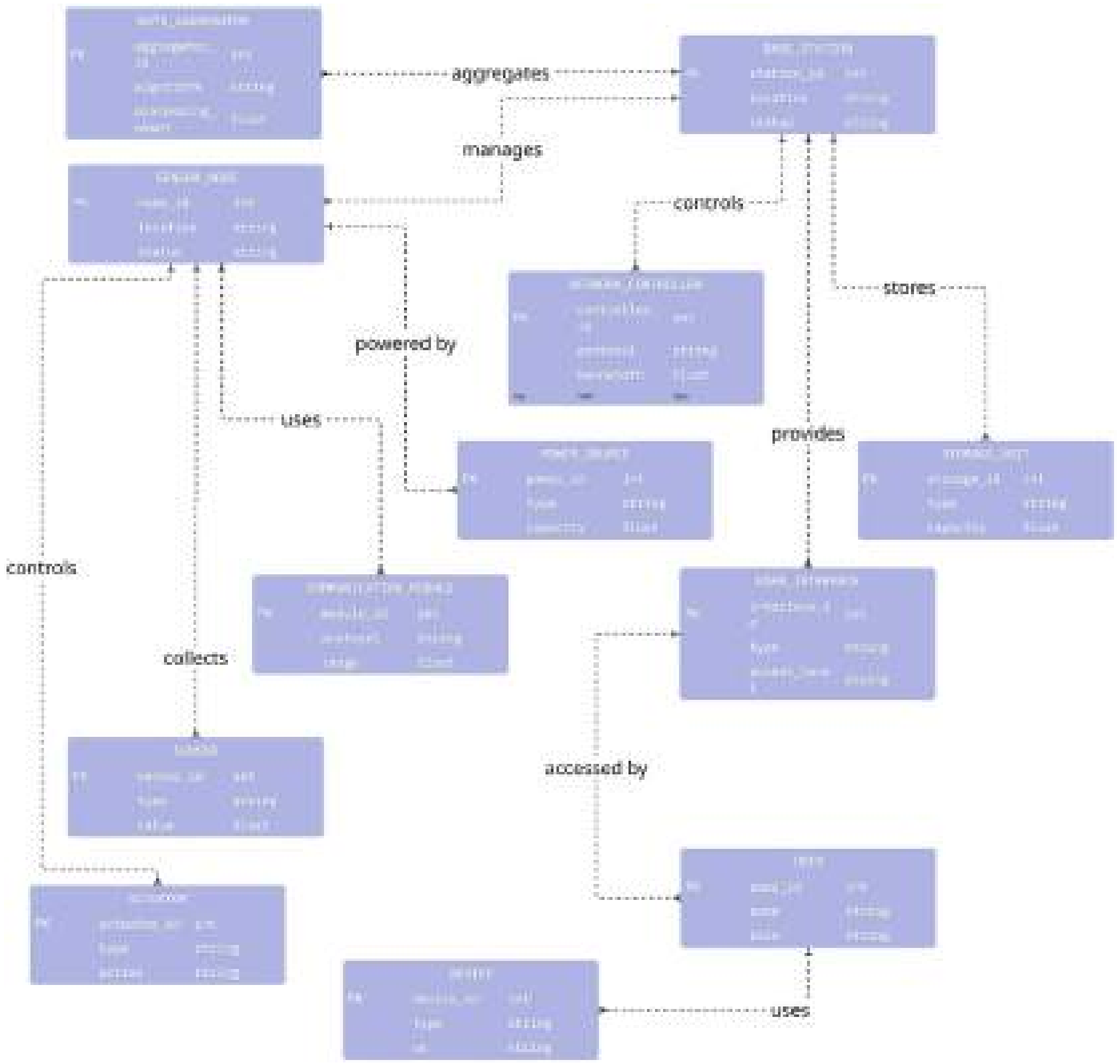

Fig. 3. Generic architecture of the logical relationships among key components of a WSN-based monitoring system.

sink nodes, highlighting data flow and communication pathways.

2.2. Operational constraints (energy, communication, computation)

Despite their benefits, WSNs are constrained by several operational limitations that directly affect their performance and reliability.

2.2.1. Energy constraints

Sensor nodes are typically powered by batteries or limited energy harvesters. Since battery replacement is often impractical; especially in remote or harsh environments; energy efficiency is a primary design consideration. Continuous sensing, communication, and idle listening rapidly drain energy, making energy-aware protocols vital for extending network lifetime [43].

2.2.2. Communication constraints

Wireless communication in WSNs is subject to signal attenuation, interference, and limited range. Multi-hop communication is used to overcome long distances, but it adds latency and overhead. Bandwidth is also limited, which necessitates data aggregation and efficient MAC and routing protocols [44].

2.2.3. Computational constraints

Sensor nodes possess limited memory and processing power due to size, energy, and cost constraints. Complex operations such as encryption, ML, or predictive analytics are typically offloaded to more powerful nodes (e.g., gateways) or cloud-based systems [45]. Lightweight algorithms are favored for in-node processing [46].

These constraints necessitate cross-layer optimization, where sensing, data transmission, and processing strategies are co-designed to maximize network performance within the bounds of resource limitations.

2.3. Performance metrics (latency, lifetime, reliability)

Evaluating WSN performance in renewable energy monitoring applications requires balancing multiple, often conflicting, metrics.

2.3.1. Latency

Refers to the delay between data generation at the sensor node and its arrival at the sink. In applications like fault detection or dynamic solar tracking, low latency is critical. Latency is influenced by routing protocol efficiency, network congestion, and MAC layer scheduling [47]. Rehman et al. (2021) addressed these challenges by proposing the Variable Traffic-Adaptive Duty Cycle Sensor MAC (VTA-SMAC) protocol, an enhancement over traditional S-MAC [48]. Their simulations demonstrated that adaptive duty cycling based on traffic load significantly reduces latency by 10.2%, 7.5%, and 18.9% under low, medium, and high traffic conditions, respectively. These improvements were achieved alongside notable energy savings, confirming the critical role of MAC-level adaptations in reducing end-to-end delay and optimizing performance in dynamic WSN environments [49].

2.3.2. Network lifetime

A crucial metric defined as the time duration until a significant portion (e.g., first or 50%) of nodes exhaust their energy. Lifetime can be extended through clustering, energy harvesting, duty cycling, and data aggregation. Protocols like LEACH, PEGASIS, and Renewable Energy-Based Routing focus on optimizing this metric [50].

2.3.3. Reliability

Measures the probability of successful data transmission from sensor nodes to the sink. It is vital for mission-critical applications, such as grid stability monitoring or predictive maintenance in wind farms. Reliability is affected by link failures, environmental noise, and buffer overflows. Redundant routing and retransmission strategies can enhance this metric [51].

Optimizing WSN performance involves trade-offs, e.g., reducing latency may increase energy consumption, while increasing reliability may require redundancy that impacts network lifetime. Therefore, application-specific protocol design is essential in renewable energy monitoring scenarios.

3. Renewable energy systems and monitoring needs

Renewable energy systems such as PV arrays, wind turbines, and micro-hydropower units are increasingly deployed worldwide to reduce carbon emissions and promote sustainable energy use [52]. However, to ensure efficient, safe, and reliable operation of these systems, real-time monitoring and control are indispensable. WSNs provide a distributed and scalable solution for collecting critical performance data from various energy systems, enabling fault detection, predictive maintenance, and performance optimization. This section outlines the specific characteristics and monitoring demands of major renewable energy systems.

3.1. Photovoltaic (PV) systems

PV systems convert sunlight into electricity using semiconductor materials such as silicon. The efficiency of these systems is highly dependent on environmental, operational factors, and the efficiency of the inverter responsible for DC-to-AC power conversion. WSNs play a pivotal role in enabling real-time monitoring and control of distributed PV installations [53]. They facilitate continuous tracking of irradiance to estimate energy yield, monitor panel surface temperatures to assess performance degradation, and detect anomalies such as hotspots or partial shading through thermal and current sensing. Additionally, WSNs contribute to maintaining inverter reliability by ensuring optimal conversion performance. The integration of wireless sensing technologies allows PV systems to implement intelligent control mechanisms, such as dynamic solar tracking, early fault detection, and long-term performance assessment. These capabilities are especially critical for remote or rooftop solar farms, where manual diagnostics and maintenance may be logistically or economically challenging [54].

3.2. Wind turbine monitoring

Wind turbines are intricate electromechanical systems that operate under harsh environmental conditions, dynamic mechanical loading, and sustained rotational stress. To ensure reliability and extend operational lifespan, continuous monitoring of various physical and mechanical parameters is essential. Key aspects include blade vibration and structural integrity, generator and gearbox performance, rotor speed, and ambient wind speed and direction [55]. WSNs offer a non-intrusive and scalable approach for capturing these parameters by utilizing accelerometers, vibration sensors, strain gauges, and anemometers installed on blades, hubs, and nacelles. The data acquired through these nodes supports predictive maintenance strategies, enabling the early detection of mechanical issues such as bearing degradation or blade fissures. Furthermore, WSNs facilitate performance optimization in response to fluctuating wind conditions and enable remote diagnostics, which are particularly valuable in offshore and mountainous wind farms where manual inspection is both difficult and costly. By eliminating the need for extensive wiring, WSNs reduce infrastructure complexity and allow for the cost-effective expansion of sensor coverage across entire turbine fields [56].

3.3. Micro-hydro and hybrid systems

Micro-hydro systems, commonly utilized in rural electrification projects, generate electricity by harnessing the kinetic energy of flowing water through small-scale turbines [57]. Micro-hydro and hybrid renewable energy systems provide reliable, decentralized power, especially in regions with steady water flow. Their effective operation depends on real-time monitoring of key parameters like water flow, turbine speed, and hydraulic head. As highlighted by Dirie et al. in 2024, dam-related infrastructure requires complex, multi-criteria assessments to ensure optimal site selection and system performance, reinforcing the need for data-driven planning and monitoring in sustainable energy applications [58]. WSNs enable distributed sensing throughout the hydro infrastructure, from water intake points to turbine outlets, and across solar or wind subsystems in hybrid configurations [59]. In such environments, WSN-based control units can facilitate intelligent source prioritization, for instance, shifting the load to solar panels during periods of low water availability. They also support the detection of abnormal operating conditions, such as turbine over-speed, and allow continuous performance logging. Hybrid systems particularly benefit from the integrative capacity of WSNs, which unify diverse data streams from various energy modalities into a centralized, real-time monitoring interface, thus enabling more effective energy management and operational decision-making [60].

3.4. Common monitoring parameters

Across all renewable energy systems there exists a core set of physical and electrical parameters that must be continuously monitored to ensure the operational integrity, safety, and efficiency of the installation (See Table 1). These parameters serve as diagnostic indicators for system performance and are essential inputs for control algorithms, performance forecasting, and anomaly detection [61]. The five most critical parameters typically include temperature, voltage, current, irradiance, and Rotations Per Minute (RPM). Temperature directly impacts the efficiency and lifespan of several system components. In solar PV systems, elevated temperatures reduce the output voltage and efficiency of PV cells, while in battery-based systems, excessive heat can accelerate chemical degradation [62]. Voltage measurement is fundamental for assessing the electrical health of PV panels, wind turbine generators, and micro-hydro alternators. It helps in identifying underperforming modules or detecting line faults. Current, when measured in conjunction with voltage, allows for the computation of power output and aids in load balancing, inverter performance evaluation, and fault detection. Irradiance is a key metric for PV installations, as it quantifies the solar energy available for conversion [63]. Accurate irradiance data enables the computation of performance ratios, capacity factor estimation, and predictive modeling of solar yield. Lastly, rotational speed is a crucial parameter for both wind and hydro turbines [64]. It reflects mechanical performance and is used to assess dynamic loads, control turbine operation within safe thresholds, and predict mechanical fatigue. These parameters are captured by analog or digital sensors strategically placed throughout the energy system and transmitted wirelessly to a BS or cloud-based platform for aggregation, visualization, and analysis. The accuracy and reliability of this data depend heavily on correct sensor calibration, placement, and environmental protection, particularly in outdoor or remote installations where conditions can be severe [65].

4. WSN communication protocols for renewable energy applications

Efficient and reliable communication protocols are fundamental to the operation of WSNs in renewable energy systems. Given the energy and computational constraints of sensor nodes, protocol design must balance latency, energy consumption, scalability, and robustness. This section provides a detailed overview of routing strategies, focusing on energy-efficient and adaptive protocols suitable for solar, wind, and hybrid monitoring environments.

4.1. Classification of WSN routing protocols

Fig. 4 presents a structured decision flowchart that compares three primary categories of routing protocols used in WSNs: Flat Routing [66], Hierarchical

Table 1. Core monitoring parameters in renewable energy systems.

Parameter	Unit	Purpose	Specific Applications & Considerations
Temperature	°C (°F)	Affects solar cell efficiency, battery health, power electronics performance, and overall component longevity; crucial for thermal management.	Solar PV: Module backsheet temperature, ambient temperature, heat sink temperature (inverters). Wind Turbines: Generator temperature, gearbox temperature, bearing temperature. Batteries: Cell temperature, module temperature, ambient temperature. Hydroelectric: Generator winding temperature, bearing oil temperature. Geothermal: Fluid inlet/outlet temperature.
Voltage	V	Indicates panel/generator health, battery state of charge, and power grid compliance; essential for system diagnostics and control.	Solar PV: Individual module voltage, string voltage, DC bus voltage, AC grid voltage. Wind Turbines: Generator voltage, grid synchronization voltage. Batteries: Cell voltage, pack voltage, DC bus voltage. Hydroelectric: Generator voltage, excitation voltage. Fuel Cells: Stack voltage, individual cell voltage.
Current	A	Enables power calculation, helps detect electrical abnormalities (e.g., short circuits, overcurrents, ground faults), and assesses load.	Solar PV: Module current, string current, DC bus current, AC grid current. Wind Turbines: Generator current, stator current, rotor current. Batteries: Charge/discharge current, string current. Hydroelectric: Generator current, field current. Fuel Cells: Stack current, load current.
Irradiance (Solar)	W/m^2	Critical for estimating solar performance ratios, predicting energy yield, and optimizing system tracking.	Measured using pyranometers or irradiance sensors, often on the plane of the array. Used for performance analysis, forecasting, and control algorithms.
Wind Speed	m/s (mph, km/h)	Directly proportional to available wind power; crucial for performance analysis, control strategies (e.g., pitch control, cut-out speed).	Measured using anemometers at hub height or other relevant locations. Used for power curve validation, energy forecasting, and structural load assessment.
RPM	min^{-1}	Essential in wind and hydro systems for assessing mechanical stress, efficiency, and operational safety of rotating equipment.	Wind Turbines: Rotor RPM, generator RPM, gearbox output shaft RPM. Hydroelectric: Turbine RPM, generator RPM. Useful for vibration analysis and early fault detection.
Power (Active & Reactive)	W, kW, MW/VAR, kVAR, MVAR	Quantifies energy generation/consumption and power factor; vital for grid integration and system performance evaluation.	Measured at various points in the system (e.g., individual generators, inverters, grid connection points). Used for billing, grid stability analysis, and optimizing energy dispatch.
Frequency	Hz	Critical for maintaining grid stability and ensuring proper operation of AC-coupled systems.	Monitored at the point of interconnection with the grid. Deviations can indicate grid disturbances or system synchronization issues.
Pressure	Pa (psi, bar)	Important for certain renewable energy technologies and auxiliary systems.	Hydroelectric: Water head pressure, penstock pressure. Geothermal: Reservoir pressure, wellhead pressure. Fuel Cells: Reactant gas pressure. Can indicate system performance and potential leaks.
Flow Rate	m^3/s (gpm, l/min)	Relevant for hydroelectric and geothermal systems, indicating the amount of energy resource available.	Hydroelectric: Water flow rate through turbines. Geothermal: Geothermal fluid flow rate. Impacts power generation capacity and system efficiency.
Tilt & Azimuth (Solar)	Degrees	Indicate the physical orientation of solar panels, crucial for optimizing energy capture.	Measured during installation and may be monitored for tracking systems. Incorrect angles can significantly reduce energy yield.
State of Charge (SoC)	%	Represents the available energy in battery storage systems.	Crucial for managing battery dispatch, preventing over-discharge, and optimizing lifespan. Estimated using voltage, current integration, and other methods.
Depth of Discharge (DoD)	%	Indicates the extent to which a battery has been discharged relative to its full capacity.	Important for understanding battery usage and predicting lifespan. Shallower discharges generally lead to longer cycle life.

(Continued)

Table 1. Continued.

Parameter	Unit	Purpose	Specific Applications & Considerations
Vibration	m/s^2, mm/s	Can indicate mechanical faults or imbalances in rotating machinery (wind turbines, hydro turbines, generators).	Measured using accelerometers. Analysis of vibration patterns and frequencies can provide early warnings of bearing failure, misalignment, or other mechanical issues.
Sound Level	dB(A)	Important for environmental monitoring and assessing the noise impact of renewable energy installations (especially wind turbines).	Measured using sound level meters at various distances. Compliance with noise regulations is often a key permitting requirement.
Water Quality (Hydro)	Various units	Affects the performance and lifespan of hydroelectric equipment (e.g., sedimentation, corrosion).	Parameters include suspended solids, pH, dissolved oxygen, and chemical composition. Regular monitoring helps prevent damage and maintain efficiency.

Routing [67], and Location-Based Routing [68]. These protocols are evaluated in terms of their architectural design, implementation simplicity, energy efficiency, scalability, and accuracy in data transmission—each of which is critical for optimizing WSN performance in renewable energy monitoring systems [69]. Flat routing protocols treat all sensor nodes uniformly, with no hierarchical differentiation; every node participates equally in routing and communication tasks based on local or global network knowledge. As depicted in Fig. 4, this approach is marked by its simplicity and ease of implementation, making it suitable for small to medium-scale networks. Flat routing supports rapid deployment and development flexibility, and its scalability can be extended through data aggregation and multi-hop transmission techniques. However, the lack of hierarchy leads to inefficiencies in large-scale deployments due to redundant data transmission and suboptimal load distribution, rendering it less ideal for utility-scale solar farms or expansive wind parks [70].

In contrast, hierarchical routing protocols—such as LEACH and PEGASIS—introduce a layered structure wherein sensor nodes are organized into clusters, each led by a designated cluster head responsible for data aggregation and forwarding [71]. This architecture significantly reduces the volume of long-distance transmissions, thereby enhancing network energy efficiency and extending node lifetimes [72]. As highlighted in Fig. 4, hierarchical protocols excel in energy conservation and load balancing by rotating the role of cluster heads and minimizing data redundancy [73]. Their ability to handle dense, geographically distributed networks makes them particularly well-suited for large-scale renewable energy applications like PV fields and wind turbine arrays, where the topological structure demands both scalability and fault tolerance [74]. Location-based routing protocols represent a third approach, relying on geographic coordinates to guide data transmission. Protocols such as Greedy Perimeter Stateless Routing (GPSR) and Geographic Adaptive Fidelity (GAF) leverage spatial information to establish efficient routes based on node proximity to the sink, thereby minimizing hop count and reducing transmission latency. As illustrated in Fig. 4, these protocols offer advantages in data delivery accuracy and node localization efficiency, especially in structured deployments where sensor placement follows regular geometric patterns such as in linear solar panel configurations or systematically spaced wind turbines. This type of routing is particularly beneficial in scenarios where nodes remain stationary and can be precisely located, enabling dynamic adaptation to topology changes and significantly reducing communication overhead.

Fig. 4 concludes with a unified "End Comparison" node, which encapsulates the collective insights drawn from the evaluation of flat, hierarchical, and location-based routing strategies. It clearly illustrates that while each protocol type offers distinct advantages, no single routing approach is universally superior across all deployment scenarios. The selection of an appropriate routing protocol must consider a combination of factors such as the size and topology of the sensor network, the availability and consistency of energy sources (including EH capabilities), the frequency and urgency of data transmission, and the level of precision and latency required by the application [75]. For example, flat routing may be most effective in compact and uniformly distributed PV systems where simplicity and ease of deployment are prioritized. In contrast, hierarchical routing protocols are better suited for large-scale or clustered deployments such as solar farms or wind turbine arrays, where energy efficiency and load balancing are critical [76]. Location-based routing proves particularly beneficial in structured environments like hybrid systems where components are spatially organized, allowing for precise and efficient data delivery [77]. Ultimately, the optimal protocol must align with the specific operational goals and constraints of the renewable energy system in which it is implemented. In practical WSN deployments, hybrid

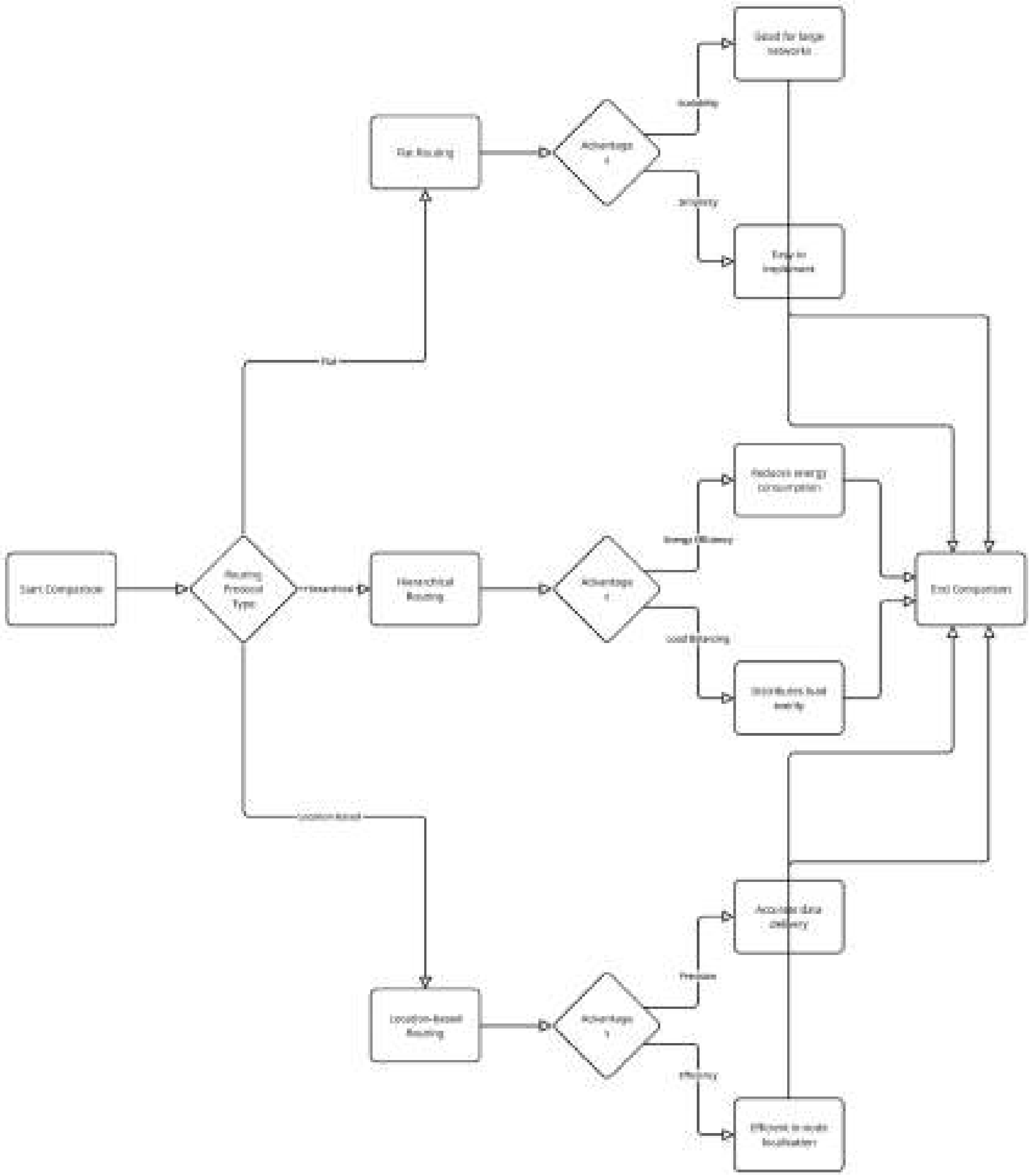

Fig. 4. Comparison of routing protocol types in WSN.

solutions that combine features from different categories (e.g., ZRP: Zone Routing Protocol) are also emerging, aiming to optimize both energy efficiency and responsiveness.

4.1.1. Proactive protocols (e.g., OLSR)

Proactive, or table-driven, routing protocols are designed to always maintain up-to-date routing information by having each node periodically broadcast routing updates [78]. This approach ensures that a complete routing table is readily available, allowing immediate route access whenever data transmission is required. A representative example of this category is the Optimized Link State Routing (OLSR) protocol [79]. The principal advantage of proactive routing protocols lies in their ability to establish and maintain routing paths in advance, thereby eliminating the latency typically associated with on-demand route discovery [80]. This makes them particularly well-suited for real-time applications where immediate data forwarding is critical, such as fault detection or dynamic solar tracking in renewable energy systems. This claim is supported by the findings of Priyambodo et al. (2021), who conducted a comparative analysis of the proactive OLSR protocol and the reactive On-Demand Distance Vector (AODV) protocol [81]. The study showed that OLSR achieved significantly lower delay than AODV, underscoring its suitability for delay-sensitive applications. Specifically, while AODV's performance could be improved through parameter tuning; yielding a 17.7% reduction in delay and 4.8% improvement in packet delivery ratio (PDR); OLSR still maintained superior latency performance without the need for additional configuration. These results validate that proactive protocols like OLSR inherently minimize delay [82], supporting real-time and continuous data transmission needs in WSN-based renewable energy monitoring systems [83]. However, this comes at the cost of high control overhead due to the continuous exchange of routing messages, which can significantly deplete node energy reserves, especially in static WSNs with low data activity [84]. As such, proactive protocols like OLSR are most effective in stable network environments characterized by frequent and regular communication demands, such as centralized PV monitoring hubs where consistent data flow is critical [85].

4.1.2. Reactive protocols (e.g., AODV)

Reactive, or on-demand, routing protocols differ from proactive approaches in that they establish routes only when data transmission is necessary. This model significantly reduces control overhead by eliminating the need for constant routing table updates, thereby conserving node energy in idle periods. A widely studied example in this category is the Adhoc AODV protocol [86]. AODV initiates route discovery dynamically through the broadcasting of route request (RREQ) messages and the receipt of route reply (RREP) messages. Reactive protocols like AODV and Dynamic Source Routing (DSR) conserve energy in low-traffic WSN environments by initiating routes only when needed, avoiding idle overhead. However, they introduce higher initial latency. Del-Valle-Soto et al. (2020) showed these protocols consume 13–16% more energy than optimized models, highlighting the trade-off between efficiency and responsiveness [87]. This latency renders reactive protocols less suitable for applications requiring strict delay constraints [88]. Nevertheless, reactive protocols like AODV are ideal for event-driven monitoring scenarios, such as wind turbine systems, where sensors activate communication only in response to specific anomalies or mechanical conditions [89], making on-demand route establishment both practical and energy-efficient [90]. For example, Medeiros et al. (2022) showed AODV's strong performance in long range (LoRa)-based networks, with an enhanced radio power adjustment (RPA) protocol achieving 11.32% power savings over DSR, emphasizing its suitability for energy-efficient, low-duty-cycle WSN applications [91].

4.1.3. Hybrid protocols (e.g., ZRP)

Hybrid routing protocols are designed to leverage the benefits of both proactive and reactive strategies by dynamically adjusting to network conditions, size, and traffic patterns [88]. These protocols aim to achieve an optimal balance between route availability and energy efficiency. A prominent example is the Zone Routing Protocol (ZRP), which partitions the network into overlapping zones [92]. Vijayalakshmi et al. (2023) support the effectiveness of hybrid routing protocols like ZRP, which combine proactive intra-zone and reactive inter-zone communication [93]. Their Random Waypoint Model enhanced ZRP to improve Quality of Service (QoS), achieving 98.595 kbps throughput and reducing latency to 0.922 seconds while maintaining a network lifetime of 346 seconds. These findings confirm that hybrid protocols offer low-latency local communication and energy-efficient long-range transmission, though they involve greater routing complexity [94]. However, these benefits come with increased architectural and computational complexity. Configuring zone sizes and managing the interaction between proactive and reactive components can be challenging, and the protocol logic may impose higher processing requirements on nodes [95]. Despite these complexities, hybrid protocols such as ZRP are particularly suitable for monitoring microgrids and hybrid renewable energy systems, where communication patterns often consist of both periodic status updates and event-driven alerts [96].

4.2. Energy-efficient clustering protocols

In renewable energy WSN deployments, clustering protocols like LEACH, PEGASIS, Threshold-sensitive Energy Efficient sensor Network (TEEN), and others are widely used to reduce communication overhead and extend network lifetime. Sensor nodes are grouped into clusters, and a CH is responsible for aggregating and forwarding data to BS.

4.2.1. LEACH

LEACH, or Low Energy Adaptive Clustering Hierarchy, is a foundational hierarchical routing protocol that introduced the concept of rotating CH responsibilities among sensor nodes to evenly distribute energy consumption and extend network lifetime [97]. The protocol operates in rounds, with CHs selected randomly to ensure no single node is overburdened [98]. Once elected, the CH aggregates data from member nodes within its cluster and transmits a summarized report to the sink, significantly reducing the number of long-range transmissions [99]. Communication within the cluster is organized using Time Division Multiple Access (TDMA) or Code Division Multiple Access (CDMA) schemes to prevent collisions and minimize energy waste [100]. The study by Jaleel et al. (2025) supports LEACH's core strength in minimizing communication overhead through local data processing [101]. By organizing sensor nodes into clusters and enabling cluster heads to perform data fusion before transmission to the base station, LEACH significantly conserves energy and extends network lifetime. Their proposed hybrid LEACH approach further reduces sensor node energy consumption, demonstrating enhanced efficiency in managing communication within WSNs [102]. However, its effectiveness is contingent on the assumption that all nodes possess equal energy capabilities, making it less suitable for networks with heterogeneous power levels [103]. To overcome these limitations, recent enhancements to LEACH have been proposed. Bhola et al. (2020) integrated a Genetic Algorithm (GA) with LEACH to optimize CH selection based on a fitness function that considers energy efficiency [98]. Their results demonstrated a 17.39% reduction in energy consumption, thereby improving network longevity. Similarly, Sambhe et al. (2025) conducted a comparative analysis between LEACH and the Harmony Search Algorithm (HSA) [104]. While HSA bypasses clustering altogether to identify energy-optimal paths, their findings reveal that LEACH remains a strong baseline, especially when enhanced by algorithmic optimization strategies. Notably, HSA achieved 9.2% better energy efficiency and extended network lifetime by 9.52%, highlighting the potential of hybrid strategies for energy-constrained environments.

4.2.2. PEGASIS

PEGASIS, or Power-Efficient GAthering in Sensor Information Systems [105], is an enhancement over LEACH that further reduces energy consumption by organizing sensor nodes into a linear chain [106]. The chain is typically formed using a greedy algorithm that selects the nearest neighbor at each step to optimize routing efficiency. However, recent enhancements have proposed more robust methods. For instance, Krishna et al. (2024) introduced the use of Prim's algorithm for hierarchical chain-based routing, enabling adaptive chain restructuring based on node energy levels and improving network lifespan by up to 22.8% compared to traditional PEGASIS [107]. A central feature of PEGASIS is the selection of a single leader node per round to transmit data to the BS, while the rest focus solely on data aggregation and forwarding. This role is dynamically rotated among nodes to distribute energy consumption evenly. Building on this, Reddy et al. (2025) proposed a PEGASIS-TEEN hybrid (PT-Hybrid) protocol that combines PEGASIS's chain-based structure with TEEN's threshold-based data reporting, further reducing unnecessary transmissions and extending network longevity [108]. The hybrid model integrates dynamic leader election and multi-hop communication, which ensures balanced energy dispersal and improved performance in real-world WSN deployments.

The protocol offers even lower energy consumption than LEACH and simplifies data management by consolidating multiple transmissions into a single, streamlined path [109]. However, the approach introduces a trade-off in the form of increased communication delay, especially as the chain length grows. Furthermore, PEGASIS is less resilient to individual node failures since the disruption of a single link can compromise the entire communication chain. It is best suited for applications in linear or narrowly structured environments, such as pipeline-based hydro monitoring systems or aligned wind turbine arrays, where the physical layout aligns naturally with the protocol's chain-based architecture.

4.2.3. TEEN and APTEEN

TEEN and APTEEN (Adaptive Periodic TEEN) are hierarchical routing protocols designed to optimize energy efficiency while supporting time-sensitive data reporting. TEEN is primarily a reactive protocol developed for applications where sudden changes in sensor readings need to be captured promptly. It achieves this by defining two thresholds: a hard threshold, which triggers data transmission when a sensed value exceeds a critical level, and a soft threshold, which fine-tunes sensitivity by limiting transmissions to significant variations in sensor readings. APTEEN, on the other hand, builds upon TEEN by integrating both periodic and threshold-based data reporting [110]. This hybrid approach allows for regular status updates while still responding to critical events, making it more flexible for a wider range of monitoring needs [111]. Both protocols contribute to significant energy savings by reducing unnecessary transmissions during periods of stability, thereby extending the network's operational lifetime. However, these benefits come with certain trade-offs. TEEN and APTEEN may overlook minor but cumulatively important fluctuations in system behavior due to their threshold-based logic. Additionally, determining and tuning the appropriate thresholds can be complex and highly application-specific. These protocols are

Table 2. Comparative analysis of WSN routing protocols for renewable energy monitoring.

Protocol	Routing Type	Lifetime	Scalability	Control Overhead	Suitability for Renewable Systems
OLSR	Proactive	Moderate	Low–Moderate	High	PV systems with frequent data polling
AODV	Reactive	High	Moderate	Low	Wind/hydro systems with event triggers
ZRP	Hybrid	High	High	Moderate	Microgrids, hybrid networks
LEACH	Clustering	High	Low–Moderate	Low	Rooftop PV, small solar systems
PEGASIS	Clustering	Very High	Moderate	Very Low	Linear arrays, wind turbine strings
TEEN	Threshold-based	High	Low	Low	Wind/hydro anomaly detection
APTEEN	Hybrid Threshold	Moderate	Moderate	Moderate	Mixed-event + periodic monitoring

particularly effective in scenarios requiring real-time fault detection, such as identifying sudden mechanical anomalies in wind turbines or detecting rapid surges in water pressure within micro-hydropower system.

4.3. Comparison table of protocols by metrics

The efficiency and viability of WSN in a renewable energy application are heavily influenced by the underlying routing protocol [112]. The choice of protocol impacts not only the network lifetime and data reliability, but also determines the system's scalability, energy consumption, and overall adaptability to environmental conditions [113]. Table 2 provides a comparative overview of several widely implemented WSN protocols across key metrics, with a focus on their suitability for different types of renewable energy systems [114].

The comparison highlights how different protocols perform across several dimensions that are critical for deploying WSNs in real-world renewable energy environments [115]. OLSR, a proactive protocol, is best suited for environments where frequent and regular data transmission is required, such as centralized PV arrays. However, it suffers from high control overhead, making it less efficient in energy-constrained networks. On the other hand, AODV, a reactive protocol, is advantageous in event-driven systems like wind or micro-hydro monitoring stations, where communication occurs only under specific conditions [116]. This results in minimal overhead and prolonged network lifetime, although it introduces some latency due to on-demand route discovery. ZRP, representing a hybrid routing approach, performs well in environments where a mix of constant and event-triggered communication is expected, such as in smart microgrids. Its scalability and adaptability make it an excellent candidate for dynamic or heterogeneous energy systems. Among clustering-based protocols, LEACH remains a foundational choice for small-scale, homogeneous networks like rooftop PV arrays due to its simplicity and localized energy management according to Mehrotra and Bhardwaj (2025) [117]. However, recent enhancements, such as the Enriched Energy Optimized LEACH (EE-OLEACH) proposed by Rajaram et al. (2025), significantly improve upon the traditional LEACH by integrating Homogeneous Hunter-Wolf Optimization (HHWO) for cluster formation and Pheromone-Profound Ant Optimization (PPAO) for optimal path selection [118]. EE-OLEACH has demonstrated substantial performance gains, including a 56% increase in network lifetime and 30% higher energy efficiency, making it a compelling choice for energy-constrained deployments. Threshold-based protocols like TEEN and APTEEN stand out in time-critical applications where immediate response to sudden changes is required. While TEEN prioritizes responsiveness with low overhead, APTEEN adds a layer of flexibility by allowing periodic data reporting, making it suitable for mixed monitoring conditions. This comparative analysis serves as a guide for selecting the most appropriate routing strategy based on the specific characteristics of the renewable energy system in question. The choice must consider trade-offs between network performance, energy consumption, and system responsiveness, as no single protocol excels in all categories [119].

5. Applications in renewable energy monitoring

The integration of WSNs into renewable energy systems has transformed the way we manage, monitor, and optimize energy generation and distribution. From PV farms to wind turbine fields and microgrid deployments, WSNs offer low-cost, flexible, and scalable solutions for data-driven decision-making. This section highlights key applications where WSNs have significantly enhanced performance, efficiency, and reliability in renewable energy environments.

5.1. Wireless monitoring of solar PV arrays

PV arrays require continuous real-time monitoring to maintain efficiency and detect faults like shading or degradation. Traditional wired systems are costly and inflexible, whereas WSN-based solutions offer a scalable, cost-effective, and adaptable alternative, ideal for rooftop and remote PV installations [120]. Recent developments demonstrate the efficacy of such WSN systems under real-world constraints. For instance, Martín et al. (2023) proposed a wireless distributed PV system using IEEE 802.15.4 and artificial vision to maintain MPP tracking above 99%, even under partial shading [121]. Similarly, Boulemzaoud et al. (2022) and Paredes-Parra et al. (2019) showcased LoRa-based WSNs offering long-range, low-power, and modular data acquisition capabilities; ideal for extensive or hard-to-reach PV arrays [122]. These systems integrate sensors for voltage, current, sun tracking, and environmental monitoring, transmitting real-time data to a gateway or central sink. That gateway, typically linked to a SCADA or cloud platform, enables data aggregation, visualization, control, and fault alerts [123]. Moreover, integration with IoT platforms facilitates remote access, as demonstrated by Pramono et al. (2017), whose system combined voltage and current sensing with internet-based relay control for fault protection and load regulation [124]. Meanwhile, energy self-sufficiency of sensor nodes is being pursued using optimized solar energy harvesting circuits with MPPT and PWM controllers, achieving up to 96% efficiency, as reported by Sharma et al. (2018) [125]. These advances reinforce the critical role of WSNs in transforming traditional PV systems into smart, autonomous, and highly efficient energy infrastructures.

Fig. 5 The schematic illustrates a WSN deployment in a solar PV farm, highlighting sensor nodes placed on individual panels to monitor environmental (irradiance, temperature) and electrical (voltage, current, power) parameters. Data is centrally aggregated via a gateway to assess panel performance and detect issues like shading or degradation. The sensor nodes process the collected data and wirelessly transmit it to a central gateway or sink node [126]. The gateway aggregates data from all sensor nodes, performs initial data processing, and forwards the information to a SCADA system or a cloud-basFed platform for further analysis and visualization. This hierarchical data flow ensures efficient monitoring and management of the PV farm's performance [127]. Implementing a WSN in a solar PV monitoring system provides multiple strategic advantages. One of the most significant is real-time monitoring, which allows for continuous data collection and the immediate detection of anomalies or performance degradation across the array [128]. This facilitates quick responses to emerging issues, thereby minimizing energy loss. The system is also inherently scalable, as its wireless nature enables straightforward expansion and reconfiguration, making it well-suited for PV farms that may grow overtime or require modular deployment [129]. Furthermore, WSN integration enhances cost-effectiveness by eliminating the need for extensive physical cabling, which not only reduces initial installation expenses but also simplifies ongoing maintenance [130]. Another important benefit is improved maintenance efficiency; by providing timely and localized fault identification, WSNs support proactive maintenance strategies, reduce system downtime, and ultimately contribute to increased energy yield and system longevity.

5.2. Wind farm sensor networks for fault detection

Modern wind turbines operate under high mechanical stress, fluctuating load conditions, and continuous exposure to harsh environmental factors, making real-time monitoring essential for maintaining operational integrity and minimizing downtime. WSNs

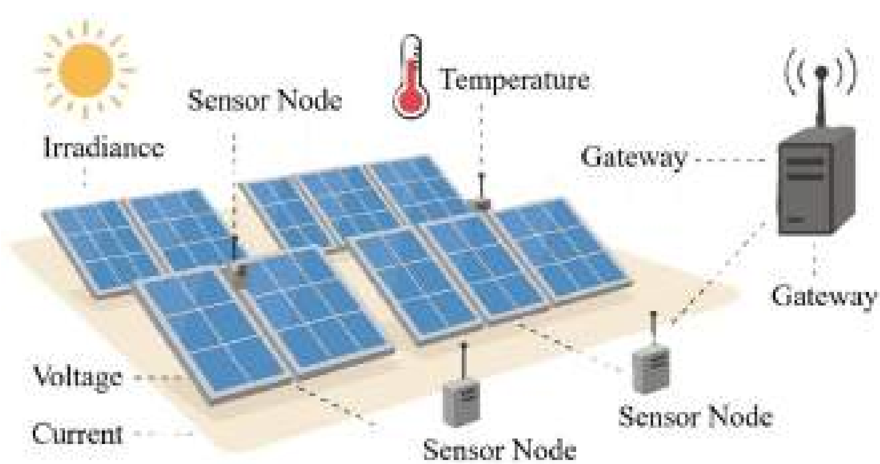

Fig. 5. WSN deployment in a solar PV monitoring system.

offer a cost-effective and scalable solution for implementing condition monitoring systems (CMS) across wind farms [131]. Typically, these CMS architectures deploy vibration and accelerometer sensors on blades and nacelles, strain gauges on rotor hubs and towers, and temperature and pressure sensors on gearboxes and bearings, along with anemometers and wind vanes for local wind tracking [132]. To address power constraints in remote installations, recent advances have explored the use of energy harvesters tailored to wind turbine environments. For example, Kan et al. (2021) introduced a magnetically coupled piezoelectric wind EH capable of adapting to different wind speeds and delivering peak power of 4.73mW, sufficient for powering sensor nodes [133]. Similarly, Izhar et al. (2023) developed a hybrid acoustic, vibration, and wind EH that produces multi-source energy, achieving 285μW at 8m/s wind speed; ideal for self-powered WSN nodes in harsh environments [134]. Fan et al. (2020) presented a triboelectric-electromagnetic hybrid nanogenerator that not only powers WSNs but also serves as a wind speed sensor, with output voltages of 416V (TENG) and 63.2V (EMG) at 15m/s [135]. These technologies enable WSN deployments in inaccessible or infrastructure-limited wind farms without dependence on batteries or grid connections.

Moreover, Akin-Ponnle et al. (2023) demonstrated that small-scale wind turbines like home chimney pinwheels could supply low-power IoT devices in urban settings [136]. While Gonchigsumlaa et al. (2020) proposed a wind-powered energy supply for WSNs monitoring freight train safety, highlighting the feasibility of wind-based harvesting for mobile and industrial settings alike [137]. These benefits are particularly valuable in challenging deployment scenarios such as offshore installations with limited physical access, remote onshore sites, or hybrid renewable energy stations in islanded microgrids, where traditional monitoring methods may be impractical or cost-prohibitive [138].

Fig. 6 illustrates a comprehensive deployment scheme for wireless sensor nodes integrated into a modern wind turbine to enable real-time structural health and performance monitoring. The diagram highlights key turbine components; including the blades, nacelle, and tower; each equipped with specific sensors that target critical operational parameters [139]. On the blades, vibration sensors are installed to detect dynamic loading, blade oscillations, and potential structural anomalies such as cracks or imbalances [140]. These sensors are vital for capturing high-frequency mechanical disturbances that may indicate fatigue or failure onset. Strain sensors are mounted both on the blade roots and along the tower structure, enabling continuous assessment of tensile and compressive stresses during turbine operation [141].

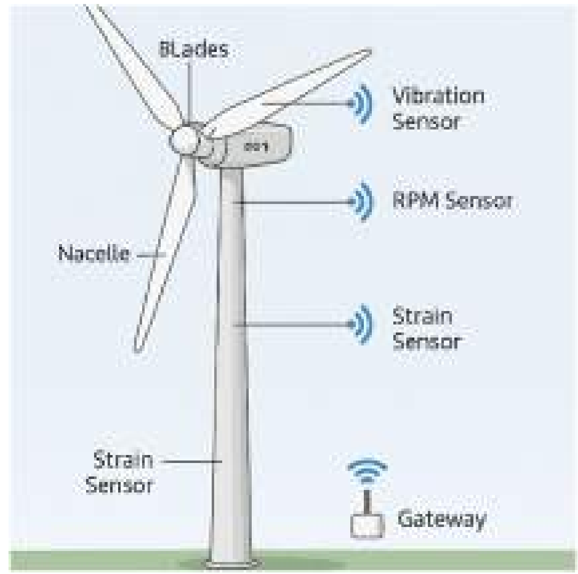

Fig. 6. Deployment of wireless sensors on a wind turbine for structural and performance monitoring.

In parallel, temperature and pressure sensors embedded in the gearbox and bearings detect thermal fluctuations and pressure anomalies that could signal lubrication issues, overheating, or mechanical degradation. These internal measurements are critical for implementing predictive maintenance strategies that prevent unexpected breakdowns and reduce costly downtimes [142]. The integration of wireless transmission capabilities allows sensor data to be aggregated and transmitted to a central controller or cloud-based system without the need for extensive cabling infrastructure [143].

5.3. Smart grid integration with IoT and WSN

When integrated with IoT technologies, WSNs enhance grid intelligence by enabling decentralized communication, automation, and data-driven decision-making [144]. These integrated systems support a wide array of critical smart grid functions [145], including accurate energy metering [146], dynamic load balancing, remote control of inverters and energy storage systems, grid synchronization, and islanding detection [147].

Moreover, they play a central role in demand-response management, allowing utilities to adjust supply in response to fluctuating load demands in real time. Applications within smart grids benefit from the ability of WSNs to capture real-time consumption data for dynamic load management

[148], facilitate seamless coordination between renewable generators and battery banks, and enable rapid fault localization and isolation in distribution networks [149]. In microgrid configurations, WSNs provide secure and efficient communication pathways between distributed energy sources and central control units [150]. To achieve these functionalities, IoT-enabled WSN nodes often incorporate advanced communication protocols such as IPv6 or MQTT, as well as edge computing capabilities to enable local decision-making at the node level. These nodes are further enhanced by cloud connectivity, which supports large-scale data analytics, AI applications, and even blockchain-based transaction recording [151]. This level of integration is already being realized in several practical use cases. In smart home environments, solar-battery systems equipped with WSN and IoT technology can autonomously manage energy flow and respond to tariff changes or grid conditions [152]. Urban and suburban renewable energy farms tied to the grid utilize WSNs for real-time monitoring, inverter control, and load forecasting [153]. On university campuses and institutional research centers, microgrids equipped with WSN-based architectures serve as testbeds for advanced energy management strategies, sustainability modeling, and intelligent fault response mechanisms [154]. The convergence of WSN and IoT in smart grid applications is thus shaping the future of intelligent energy systems [155], enabling resilience, efficiency, and sustainability at scale [156].

Fig. 7 presents an Entity Relationship (ER) model that outlines the logical structure and data flow within a smart microgrid system integrated with a WSN and IoT devices [157]. The diagram encapsulates the interactions among core system components; smart microgrids, WSNs, sensor nodes, IoT devices, data analytics platforms, and user interfaces [158]. The SMART MICROGRID–WSN–IoT structure mirrors Hemavathi and Latha's HFLFO framework, where sensor nodes with defined energy and roles enhance communication [159]. Their model improved packet delivery by 17% and reduced loss by 10%, validating the importance of structured node attributes and IoT integration for efficient, QoS-optimized microgrid monitoring. Sensor nodes in the grids are responsible for environmental or electrical parameter acquisition and are directly linked to IOT_DEVICE entities that connect them to the broader IoT ecosystem [160]. IoT devices are categorized by device ID, device Type, and status, and act as communication and control interfaces between the physical sensor network and digital analytics systems [161]. Sensor data is processed and interpreted by the DATA_ANALYTICS entity, which includes fields such as analytics ID, algorithm, and result. This layer implements algorithms; potentially AI or ML-based; to extract actionable insights from the raw sensor data. These analytics outcomes are then displayed through the USER_INTERFACE, an entity that defines user access via attributes like interface ID, interface Type, and access Level. The directional relationships in the diagram depict a logical flow of interaction: the smart grid utilizes a WSN, which in turn employs sensor nodes that connect through IoT devices [162]. These devices feed data to the analytics layer, which displays results on a user interface, and the system controls the smart microgrid operations based on the insights derived.

5.4. Case studies and deployment examples

These implementations illustrate how WSNs have been instrumental in improving energy access, enhancing system performance, and enabling predictive management strategies. One significant case study involves WSN-based solar microgrids deployed for rural electrification in India and Sub-Saharan Africa [163]. In many off-grid regions within these areas, standalone solar microgrids, monitored by WSNs, have revolutionized energy access for underserved communities. Sensor nodes were installed to track power generation from PV modules, monitor the state of charge (SOC) in battery storage units, and assess inverter performance. Data collected from these nodes was transmitted wirelessly to a central gateway, often utilizing communication protocols such as ZigBee or LoRaWAN [164]. This setup enabled the central control unit to process and analyze system conditions in real time. The outcomes of this deployment were transformative. Communities experienced a significant reduction in energy theft and load imbalance, improved their household-level energy budgeting capabilities, and benefited from enhanced system reliability through remote diagnostics facilitated by GSM-connected gateways.

A relevant example is the Ukraine case, where cyber-attacks on centralized grid systems, including those that caused large-scale blackouts, revealed the vulnerabilities of traditional SCADA architectures. In response, a Proof of Authority (PoA)-based Ethereum blockchain integrated with WSNs was implemented to secure data communication and enhance resilience. The system was tested across IEEE 14-bus, 30-bus, and 118-bus models. Almasabi et al. in 2024 showed a marked improvement in data integrity and transmission reliability, with statistical metrics such as mean packet delay reduced to under 10 ms, skewness approaching 0.01, and confidence

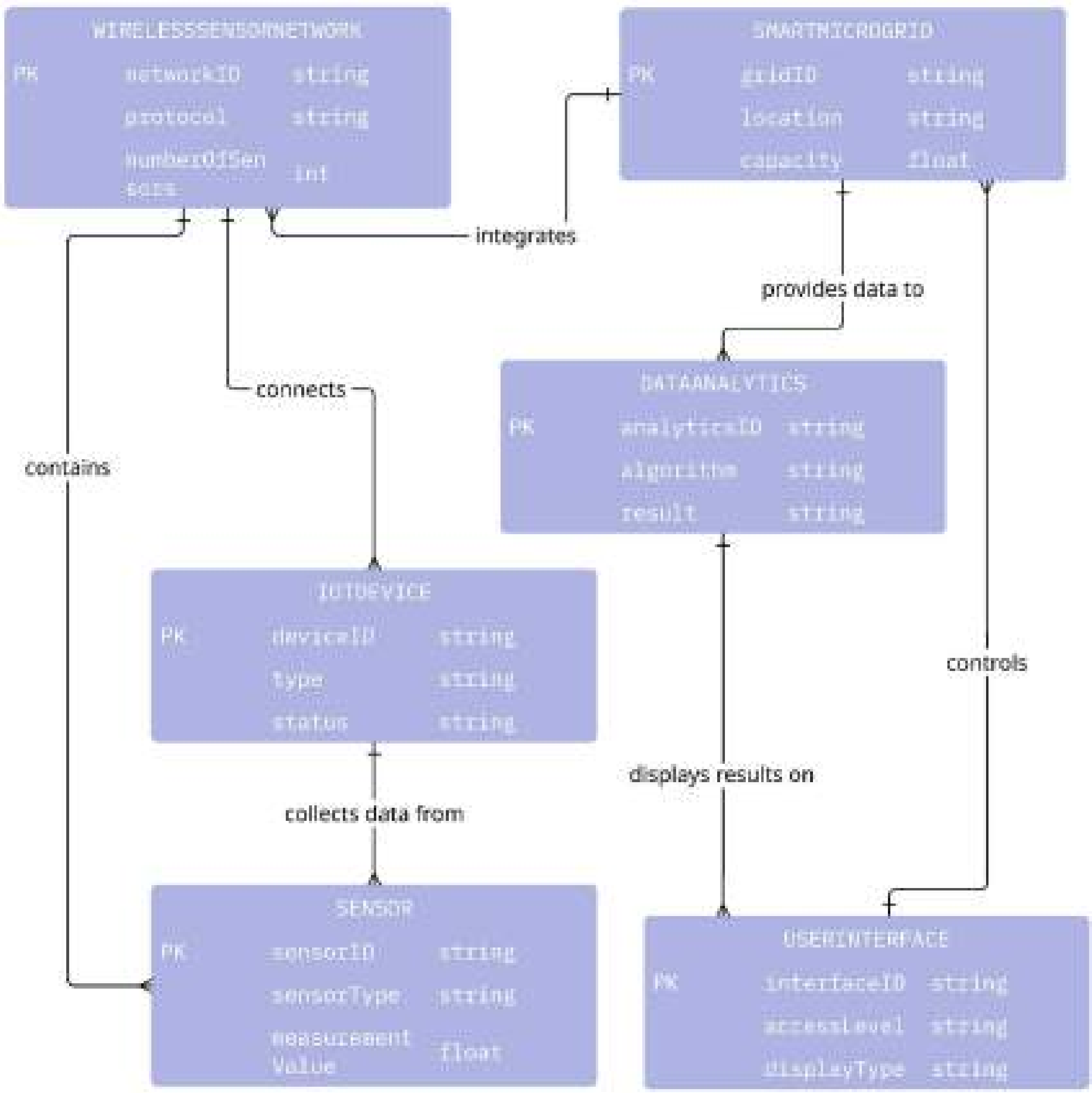

Fig. 7. Entity relationship model of IoT-WSN-based smart microgrid monitoring system.

intervals exceeding 95% for blockchain-verified sensor data [165].

Another impactful example is the application of WSNs in wind turbine monitoring across Europe's offshore wind farms. Projects such as WindNODE in Germany and the Beatrice Offshore Wind Farm in Scotland have integrated wireless sensors into turbine blades, nacelles, and gearboxes [166]. The objective was to detect mechanical anomalies at an early stage and optimize preventive maintenance schedules using continuous data streams. Real-time analytics of vibration, strain, and thermal data allowed operators to predict failures before they occurred, substantially improving overall turbine uptime; often exceeding 95% operational availability. The deployment also resulted in a 20 to 30 % reduction in operations and maintenance costs and significantly improved worker safety by reducing the need for manual inspection in difficult offshore environments. A third case study is drawn from the United States, where smart grid pilot programs such as the one implemented by PG&E in California, used WSNs to enhance grid reliability and efficiency [167]. In this initiative, WSN nodes were deployed across PV arrays, smart electricity meters, and utility substations. These nodes were IoT-enabled and configured to transmit real-time data to centralized cloud dashboards [168]. The resulting data ecosystem allowed grid operators to implement intelligent load balancing, manage the integration of electric vehicle (EV) charging stations, and quickly respond to grid disturbances. The outcomes were measurable and impactful: the grid experienced a 12%

reduction in peak load demand, a significant increase in the penetration of renewable energy sources, and improved grid resilience through automated voltage regulation and fault detection across service districts. These examples underscore the transformative potential of WSNs in real-world renewable energy scenarios. Whether in resource-limited rural environments or technologically advanced urban smart grids, WSNs offer a scalable, intelligent solution for real-time monitoring, fault prevention, and efficient energy management [169].

Another notable real-world example is the Anholt offshore wind farm in Denmark, which utilizes a software-defined IIoT–Edge network supported by Software-Defined Networking (SDN) and Network Functions Virtualization (NFV) technologies [170]. In this deployment, over 250 Ethernet switches across 111 wind turbines aggregate and route sensor data; including thermal and mechanical metrics; via fiber-optic links to a centralized data-processing center. This architecture supports real-time diagnostics and maintenance operations, while also enabling secure, scalable, and highly customizable communication across the entire wind park network [171]. Such examples highlight the vital role of advanced networking technologies in enhancing condition monitoring and operational efficiency in modern wind energy systems [172]. Ultimately, this configuration supports proactive decision-making and enhances the overall safety, reliability, and efficiency of wind energy systems [173].

6. Challenges and opportunities

Despite the vast potential of WSNs in enhancing renewable energy system monitoring and management, several operational, environmental, and scalability challenges must be addressed to ensure long-term effectiveness and deployment viability. Simultaneously, new frontiers in AI, edge computing, and next-generation communication networks (e.g., 6G) present transformative opportunities for smart and resilient energy systems [174].

6.1. EH techniques and node sustainability

A fundamental limitation in the deployment and long-term sustainability of WSNs is the restricted power supply available at sensor nodes. Most conventional WSNs rely on batteries, which have finite energy storage and require regular maintenance or replacement. This dependency becomes a major obstacle in remote, expansive, or hazardous environments where access is limited, and servicing is costly or dangerous. To address this issue, EH technologies are increasingly being integrated into sensor node designs. These technologies enable nodes to extract and convert ambient energy sources, such as solar radiation, wind movement, vibrational energy, and thermal gradients, into usable electrical power. However, the application of EH introduces several operational challenges. Ambient energy sources are inherently intermittent and unpredictable; for instance, solar and wind inputs can vary significantly due to weather conditions or environmental obstructions. Moreover, non-solar sources like mechanical vibrations tend to produce lower and less consistent energy yields. A frequent challenge is the mismatch between the timing and quantity of harvested energy and the sensor node's real-time power demands. Despite these limitations, promising opportunities exist. The adoption of hybrid storage solutions, combining supercapacitors with traditional batteries, offers effective energy buffering to stabilize power availability. Advances in predictive energy management algorithms allow sensor nodes to schedule their activities based on expected energy inflow, improving operational reliability [175]. Additionally, the use of duty cycling, and ultra-low-power communication protocols helps reduce the baseline energy consumption of each node. Ongoing research is focused on the development of energy-aware routing protocols and adaptive sampling strategies that dynamically align node behavior with harvesting conditions. These innovations are critical for enabling autonomous, maintenance-free operation of WSNs in large-scale and mission-critical renewable energy applications.

6.2. Harsh environmental conditions and maintenance

The deployment of WSNs in renewable energy systems often takes place in physically demanding environments that introduce significant operational and maintenance challenges. Renewable energy installations such as solar farms in desert regions, offshore wind turbines exposed to saline air, and high-altitude wind farms in mountainous terrain are all subject to environmental extremes. These locations frequently experience high thermal loads, moisture infiltration, salt-induced corrosion, and intense mechanical stress due to wind-driven vibrations and the rotational motion of turbine blades. Such conditions accelerate the degradation of sensor components and jeopardize data reliability and transmission integrity. Sensor drift, corrosion of exposed elements, and mechanical wear over time contribute to measurement inaccuracies and eventual device failure. Additionally, access to sensor nodes for routine maintenance or recalibration is often impractical, dangerous, or economically unviable in these remote or harsh settings. Despite these challenges, new technological advancements are opening avenues for increased resilience and reduced maintenance dependence. The development of ruggedized sensor nodes with high ingress protection (IP) ratings—such as IP68—and the incorporation of self-cleaning, hydrophobic, or anti-corrosive coatings have shown promise in extending sensor lifespan. Moreover, the integration of self-diagnostic mechanisms within sensor nodes enables systems to report their own performance degradation, allowing for proactive maintenance planning without direct inspection. The use of contactless sensing technologies, including optical or magnetic sensors, further reduces mechanical fatigue by eliminating moving parts or friction-prone interfaces. Current research efforts are focused on designing fully autonomous, maintenance-free WSN nodes capable of withstanding environmental stressors for operational periods of five to ten years. These nodes aim to incorporate self-healing materials, long-life energy storage, and sealed packaging solutions, thereby ensuring uninterrupted data acquisition and system monitoring in even the most unforgiving deployment environments.

6.3. Scalability in large-scale energy farms

As renewable energy installations grow and complexity, the scalability of WSNs becomes a critical design consideration. In utility-scale solar farms and expansive offshore wind installations, the number of deployed sensor nodes can range from dozens to several thousands. This expansion introduces significant technical bottlenecks that impact the network's efficiency and reliability. The increase in node density results in greater communication overhead due to the volume of routing information and sensor data that must be exchanged and aggregated. Higher node counts can also lead to network congestion, increased risk of packet collisions, and degraded synchronization among distributed nodes, which compromises the accuracy of time-stamped data and coordinated sensing activities. Furthermore, as the number of data-generating nodes increases [176], the energy required for multi-hop communication escalates, leading to higher power consumption and reduced network lifetime [177]. BSs may also become overwhelmed with incoming data, creating processing and transmission bottlenecks that further hinder system performance. To mitigate these challenges, several scalable architectural strategies have been explored. Cluster-based hierarchical routing protocols, such as LEACH and Hybrid Energy-Efficient Distributed (HEED) Clustering [178], have proven effective in organizing large networks into manageable units with designated CHs responsible for data aggregation and transmission [179]. Additionally, the use of mobile sinks, such as drones or autonomous ground vehicles, offers a dynamic approach to data collection, particularly in areas where fixed infrastructure is impractical. These mobile collectors can reduce communication distance and energy usage by approaching sensor clusters directly. Integration with LPWANs, including technologies like LoRa and NB-IoT, provides another layer of scalability by enabling long-range, low-power communication for dispersed nodes without relying on dense relay structures [180]. Current research is increasingly focused on the development of self-organizing topologies that adapt to node distribution and density, along with intelligent data prioritization mechanisms that distinguish between real-time operational data and lower-priority archival information. Such innovations are essential to ensuring that WSNs remain robust, efficient, and sustainable as the scale of renewable energy deployments continues to expand globally.

6.4. Future trends: AI-based optimization, edge computing, and 6G

The evolution of WSNs in renewable energy applications is being significantly accelerated by emerging technologies that address longstanding limitations related to energy efficiency, latency, scalability, and autonomous control. Among the most transformative trends are AI, edge computing, and sixth-generation (6G) communication networks, each of which contributes to building smarter, more adaptive, and self-sustaining sensor infrastructures [181]. AI, particularly in the form of ML, is being increasingly adopted to optimize WSN operations. Predictive models can be trained to forecast energy output based on historical data, detect performance anomalies in near real-time, and intelligently manage sensor duty cycles to conserve energy. Reinforcement learning algorithms have shown particular promise in enabling sensor nodes to dynamically adjust their routing paths and power usage in response to environmental changes and network conditions. For instance, in large PV arrays, AI-driven WSNs can autonomously identify underperforming modules by analyzing patterns in irradiance and current data [182], triggering localized alerts or adjustments without human intervention [183]. Edge computing is another powerful enabler of real-time decision-making in WSN deployments. By embedding microcontrollers or lightweight AI accelerators directly into sensor nodes, data can be processed locally rather than being transmitted continuously to a centralized server [184]. This approach significantly reduces latency, minimizes bandwidth usage, and enhances system responsiveness. Edge-enabled WSNs are particularly valuable in applications requiring immediate responses, such as switching between energy sources in hybrid systems, isolating faulty components, or activating load-balancing protocols based on localized conditions [185]. Looking further ahead, the integration of WSNs with 6G communication technologies is expected to revolutionize the scale and performance of renewable energy monitoring networks [186]. Features anticipated in 6G include sub-millisecond latency, integrated sensing and communication capabilities, and energy-aware MAC scheduling. These capabilities will enable ultra-reliable low-latency communication (URLLC), allowing WSNs to support critical control functions and time-sensitive applications with unprecedented precision [187]. Furthermore, 6G will facilitate massive device connectivity, potentially accommodating up to 100 times more nodes/km^2 than current standards, making it ideal for large-scale solar and wind farms. One promising avenue involves the use of intelligent spectrum allocation to improve communication efficiency and adaptability in dynamic wireless environments. Simultaneously, blockchain technology is being employed to secure and validate data exchanges in distributed energy systems [188]. For instance, Faheem et al. (2024) propose a blockchain-based framework that ensures resilient and secure event monitoring and control in decentralized renewable infrastructures, addressing vulnerabilities in conventional smart grid communications [189]. Moreover, federated learning is gaining traction as a decentralized AI approach that allows WSN nodes to train models locally without transferring raw data, thereby preserving privacy, and reducing communication overhead. In a study by Gebremariam et al. (2023), the use of federated learning for malicious node detection in IoT-based WSNs achieved 100% accuracy in binary classification and 99.95% in multiclass scenarios, highlighting its robustness for real-time threat detection and secure localization [190]. Collectively, these innovations mark a shift toward self-organizing, cyber-resilient, and highly autonomous WSNs that will underpin the next generation of optimized, adaptive, and intelligent renewable energy systems [191].

7. Discussion

This review has synthesized the current landscape of WSNs in the context of renewable energy monitoring, emphasizing their structural diversity, communication protocols, real-world applications, and integration with emerging technologies. WSNs offer a transformative platform for real-time, distributed monitoring, but their deployment success hinges on addressing critical challenges related to power efficiency, scalability, environmental resilience, and data reliability. From an architectural perspective, WSNs demonstrate high adaptability, allowing seamless integration into solar, wind, hydro, and hybrid systems. Yet, the efficiency of these networks is heavily influenced by the choice of routing protocol. Proactive protocols like OLSR provide low latency but incur high energy overhead, while reactive protocols such as AODV offer better energy management at the cost of initial latency. However, these protocols still face limitations in dynamic environments, particularly in their ability to cope with node failures, changing energy profiles, and fluctuating data transmission rates. Case studies reviewed in this work reinforce the versatility and field applicability of WSNs in diverse geographic and infrastructural settings. For instance, in rural microgrids, WSNs have enabled reliable access to electricity while reducing operational costs [192]. In contrast, large-scale offshore wind farms benefit from WSN-driven predictive maintenance, which reduces equipment downtime and enhances safety. These real-world deployments confirm that WSNs are not merely theoretical solutions but viable technologies already impacting energy systems on the ground. However, as renewable energy networks grow in size and complexity, the issue of scalability becomes increasingly pronounced. Traditional WSN architectures struggle under the demands of high node density, communication congestion, and centralized data processing. Addressing this requires a paradigm shift, one that incorporates edge computing for distributed analytics, AI for adaptive resource management, and 6G communication for ultra-reliable low-latency data exchange. Together, these technologies redefine the capabilities of WSNs, transitioning them from simple monitoring tools into autonomous, intelligent, and self-organizing agents within the energy ecosystem.

Fig. 8 presents a structured overview of the principal challenges confronting the deployment of WSNs in renewable energy systems, alongside strategic technological solutions aimed at mitigating these limitations. As WSNs become increasingly integral to solar, wind, hydro, and hybrid energy infrastructures, understanding and addressing these systemic barriers is essential for achieving long-term operational success and reliability. One of the foremost challenges highlighted is the limited power availability at sensor nodes, especially in remote or off-grid environments. Battery-powered nodes, while common, are not

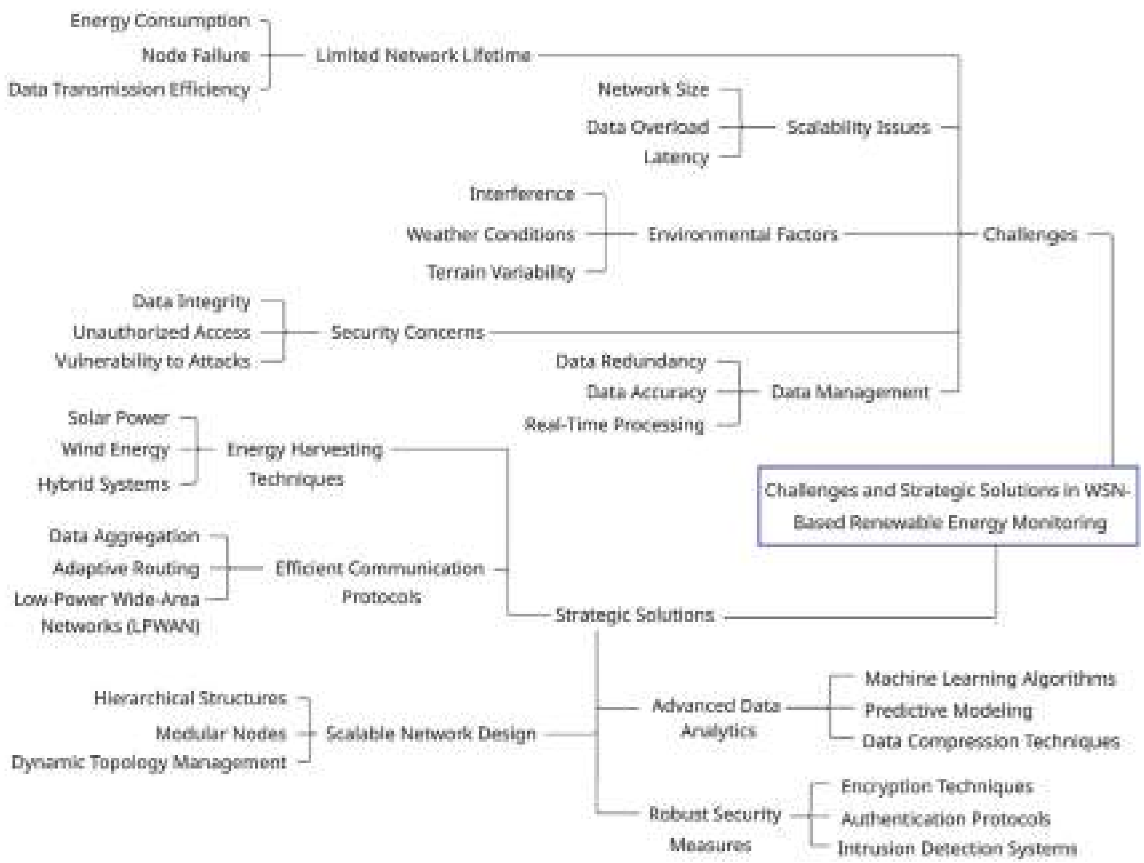

Fig. 8. Challenges and strategic solutions in WSN-based renewable energy monitoring.

sustainable in the long term due to their need for periodic maintenance and replacement. To address this, EH technologies, such as solar, vibrational, and thermal sources, are being integrated into node designs. These are further supported using supercapacitors and hybrid storage systems, which provide enhanced energy buffering capabilities. Complementary to this are ultra-low power communication protocols and duty cycling techniques that drastically reduce baseline power consumption. Another persistent issue is harsh environmental exposure, particularly in offshore wind farms, desert solar installations, and high-altitude hydroelectric systems. In such settings, factors like extreme temperatures, humidity, salinity, and mechanical stress can degrade sensor accuracy and hardware reliability. Solutions in this domain include the development of ruggedized sensors with IP68+ enclosures, as well as self-cleaning coatings and contactless sensing technologies that minimize mechanical fatigue. Future devices are expected to incorporate self-diagnostic and self-healing mechanisms to ensure long-term autonomous operation. Scalability poses a third major challenge, particularly in large-scale deployments with thousands of sensor nodes. Increasing node density leads to higher communication overhead, data collisions, and congestion, all of which degrade network performance. Strategies such as cluster-based hierarchical routing protocols (e.g., LEACH, HEED), the deployment of mobile data sinks (e.g., drones), and the integration of LPWANs offer promising solutions by enhancing communication efficiency and reducing the energy load on individual nodes. The need for real-time data analytics introduces another layer of complexity, especially when latency-sensitive decisions; such as fault detection, energy source switching, or grid stabilization; are required. Edge computing and embedded AI accelerators are being used to process data locally at the node level, reducing dependence on centralized servers and significantly decreasing communication latency.

Fig. 9 illustrates a flowchart capturing the evolutionary pathway of WSN architectures as applied to renewable energy systems, with a focus on the decision-making logic guiding system upgrades, integration with various energy sources, and performance optimization [193]. This visual framework encapsulates how WSNs evolve from initial deployment

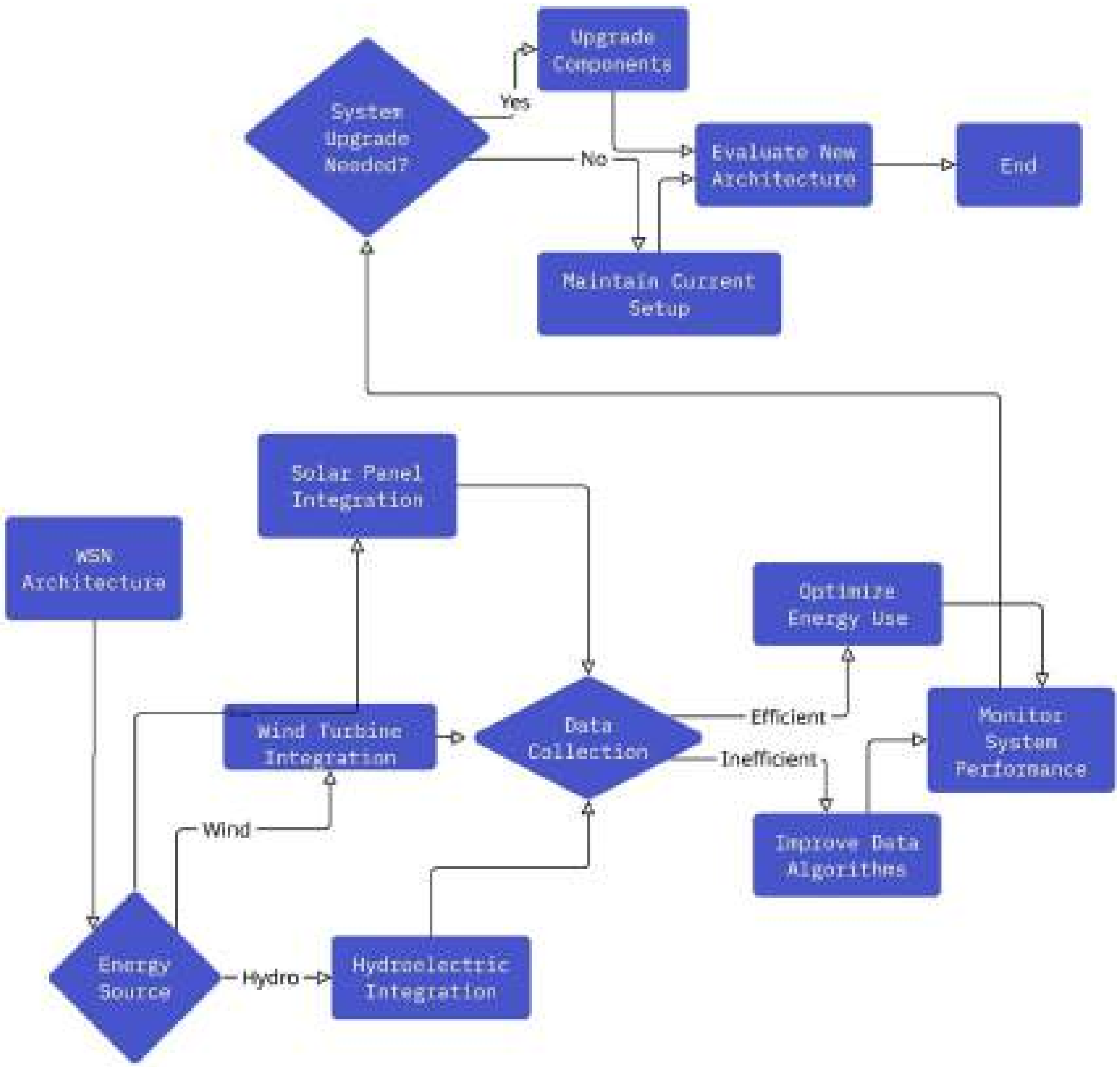

Fig. 9. Evolution of WSN architectures in renewable energy systems.

through iterative refinements based on efficiency assessments and system requirements. The diagram begins with the evaluation of system status; whether an upgrade is needed. If the system meets current performance expectations, it continues operating under the current configuration. Otherwise, it branches into component upgrades or full architectural reassessment, reflecting a critical step in adaptive system design. This flexibility is fundamental to the sustainability of WSNs in dynamic environments such as renewable energy farms, where hardware aging, technological advancements, and environmental stressors may necessitate iterative system improvements. The flow continues with the integration of WSNs into specific energy infrastructure types. These pathways underscore the modularity and adaptability of WSN architecture, which must accommodate different EH and operational characteristics [194]. For example, WSN integration with wind turbines may emphasize vibration sensing and RPM monitoring, while hydroelectric systems require flow and pressure data collection. This modular structure supports scalability and allows targeted enhancements in both hardware and software layers. At the heart of the system evolution is data collection, which serves as the operational hub linking sensor integration to performance optimization. The diagram distinguishes between efficient and inefficient data handling, prompting adaptive responses. When inefficiencies are detected, the flow directs toward improving data algorithms; highlighting the growing role of ML [195], edge computing, and predictive modeling in managing complex sensor datasets. These improvements feed into the loop of optimizing

Table 3. Summary of key WSN challenges and emerging solutions in renewable energy systems.

Challenge	Impact	Emerging Solution
Power constraints	Frequent maintenance, short lifetime	Solar/vibration harvesting, ultra-low power MCU, energy-efficient routing protocols, duty cycling, sleep scheduling
Network scalability	Congestion, reduced performance	Clustering, mobile sinks, LPWAN (LoRa, Sigfox), hierarchical routing, data aggregation, fog computing
Harsh environmental exposure	Sensor failure, data drift	IP68 sensors, self-healing materials, robust packaging, redundancy, calibration techniques, environmental monitoring
Real-time decision requirements	Latency, reliance on central control	Edge AI, local analytics, fog computing, distributed processing, low-latency communication protocols, time-sensitive networking (TSN)
Data security and decentralization	Vulnerability to attacks, privacy issues	Blockchain, federated learning, homomorphic encryption, secure routing protocols, intrusion detection systems, access control mechanisms
Reliability and Fault Tolerance	Data loss, network downtime	Redundant nodes, alternative routing paths, self-healing capabilities, dynamic network reconfiguration, robust communication protocols
Interoperability	Integration with existing systems, data format incompatibility	Standardized protocols (e.g., IEEE 802.15.4), middleware, API integration, data translation techniques
Deployment and Maintenance	Complex installation, difficult access, high costs	Self-organizing networks, remote management tools, wireless configuration, modular design, plug-and-play sensors
Data Management	Large data volumes, storage limitations	Data compression, data filtering, edge computing, cloud storage, efficient data indexing, data fusion
Localization and Time Synchronization	Inaccurate location information, unsynchronized events	GPS-less localization techniques, time synchronization protocols, beacon-based synchronization, distributed time synchronization

energy use and monitoring system performance, both of which serve as feedback mechanisms to inform future upgrades. The cyclical nature of this process embodies the core principle of self-optimizing, intelligent WSN architectures. As performance is monitored, decisions are made about whether to maintain, enhance, or redesign the system, forming a continuous loop of evaluation, adaptation, and evolution. This approach reflects modern trends in smart grid and IoT-integrated energy systems, where real-time data and computational intelligence drive system-wide improvements [196]. In essence, Fig. 9 demonstrates that WSN evolution in renewable energy contexts is not linear but cyclic and data-driven, centered around ongoing evaluation of performance, contextual integration with energy sources, and incremental algorithmic and architectural enhancements. This adaptability is what makes WSNs a critical enabler of future-proof, intelligent renewable energy infrastructures.

Table 3 and Fig. 10 present a concise, yet comprehensive overview of the principal challenges associated with deploying WSNs in renewable energy systems, along with emerging technological solutions that are being developed to mitigate their impacts. These challenge–solution pairs reflect both the practical constraints encountered in real-world energy monitoring environments and the cutting-edge innovations aimed at overcoming them. Power constraints remain one of the most fundamental limitations in WSN operation, particularly in remote or off-grid deployments [197]. Conventional battery-powered sensor nodes demand frequent maintenance and have limited operational lifespans, which compromises network reliability and scalability [198]. To address this, emerging solutions focus on integrating EH mechanisms such as solar, vibrational, and thermal energy sources, coupled with the development of ultra-low-power microcontrollers (MCUs) that can operate efficiently under variable power conditions. These technologies significantly reduce the need for human intervention and enhance long-term sustainability. Network scalability becomes increasingly important as renewable energy installations grow in size and complexity [199]. Large-scale PV farms or wind turbine arrays may require thousands of sensor nodes, leading to network congestion, increased latency, and reduced communication reliability [200]. Hierarchical clustering protocols (e.g., LEACH), the use of mobile sinks (e.g., drones), and the deployment of LPWANs such as LoRa and NB-IoT offer viable solutions by reducing communication overhead and extending coverage without compromising data throughput [201].

Harsh environmental exposure presents another major challenge, particularly in offshore wind farms,

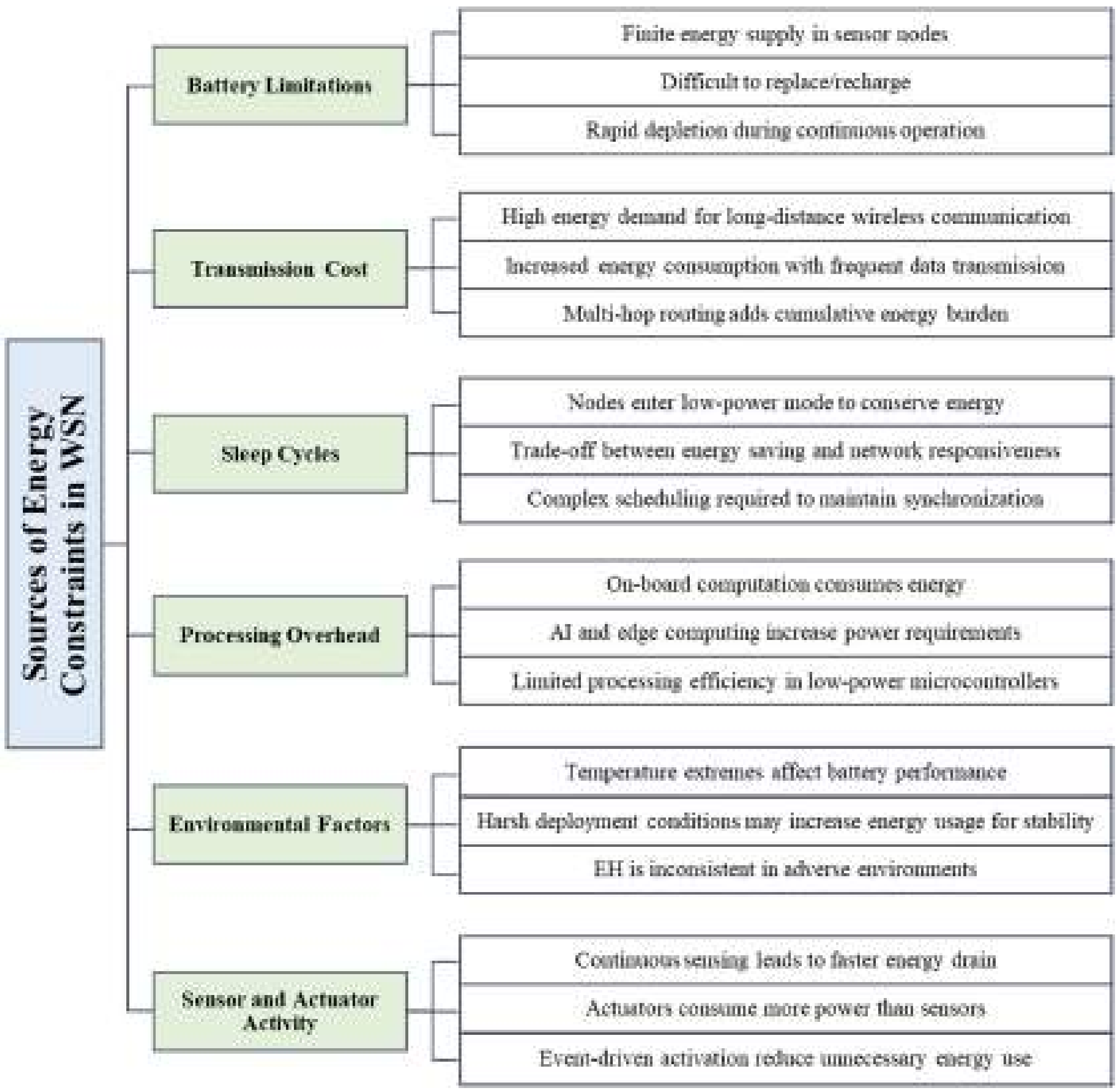

Fig. 10. The primary sources of energy constraints in WSNs, including transmission costs, battery limits, and environmental effects.

desert solar fields, and high-altitude hydroelectric installations. Environmental stressors such as salinity, extreme temperatures, and mechanical vibrations can cause sensor failures or lead to data drift over time. In response, research has advanced toward ruggedized sensor designs with IP68 ratings, corrosion-resistant materials, and self-healing components capable of sustaining accurate operation over extended periods with minimal degradation. The requirement for real-time decision-making in grid operations introduces latency challenges and places strain on centralized architectures. Renewable systems increasingly depend on immediate fault detection, energy balancing, and load shifting; all of which require low-latency, decentralized analytics. Edge computing and embedded AI algorithms at the node level enable local decision-making without round-trip communication to central servers. This not only improves responsiveness but also reduces bandwidth demands and increases system resilience. Finally, data security and decentralization are emerging concerns as WSNs become integral to critical infrastructure. Sensor networks are susceptible to attacks, unauthorized access, and data breaches, especially when they interface with public communication systems or cloud platforms. Blockchain technology provides a secure framework for validating and recording sensor data, while federated learning allows decentralized AI model training without compromising user or system privacy. Together, these technologies ensure robust, scalable, and secure sensor network architectures aligned with modern cybersecurity demands.

Future research should focus on integrated system co-design, where energy harvesting, routing protocols, security mechanisms, and analytics platforms are developed in unison. Additionally, the role of federated learning and blockchain in creating secure, decentralized, and privacy-preserving sensor networks must be further explored. Ultimately, the goal is to build resilient, low-maintenance WSNs capable of operating autonomously for years, especially in remote and hostile environments where human intervention is impractical.

8. Conclusion

The reviewed literature strongly supports the pivotal role of WSNs in transforming traditional renewable energy systems into smart, automated, and energy-efficient infrastructures. In the PV domain, WSNs enable module-level monitoring to detect shading, soiling, and hot spots, using both centralized and distributed sensing architectures. Protocols like LEACH and its optimized versions have been effectively applied in rooftop PV and microgrid systems, where network homogeneity and spatial compactness align with the protocol's design assumptions. In wind energy applications, especially in offshore and hybrid stations, PEGASIS-based and SDN-integrated systems are more suitable due to their ability to handle long-range, large-scale deployments. These systems ensure reliable data aggregation from remote turbine components, including gearbox temperature sensors and blade strain gauges, with SDN enhancing network agility, traffic management, and O&M support. Hydropower monitoring systems and time-sensitive applications benefit from TEEN and APTEEN, which allow for threshold-based alerts, especially during sudden load surges or water level fluctuations. Their minimal latency and event-driven designs ensure faster response times, crucial for protective relaying and safety mechanisms. Furthermore, emerging technologies like blockchain and federated learning introduce resilient, decentralized, and secure data management to WSNs, particularly in scenarios involving multi-source DERs, where cybersecurity and data integrity are critical. The literature also shows increasing interest in energy harvesting (e.g., piezoelectric, wind, and vibration-based systems) to ensure sensor self-sustainability in inaccessible locations.

Despite these advancements, several gaps remain:

1. Technologies like Edge computing, 6G, and federated learning are often presented with optimistic outlooks, but their integration maturity within WSN-based renewable systems is underexplored. Few studies critically assess the infrastructure requirements, latency constraints, or computational limitations of deploying these solutions in resource-constrained WSN nodes.
2. Much of the research relies on simulations (e.g., MATLAB, NS-2) rather than field-deployed results, limiting the assessment of real-world challenges such as environmental noise, interference, and sensor node failure.
3. While blockchain-based frameworks are emerging, comprehensive comparative evaluations of lightweight cryptographic techniques suitable for WSN nodes in energy-scarce environments are limited.
4. Current protocols often optimize either routing, MAC, or application layers independently, but coordinated cross-layer designs could yield better energy efficiency and performance.
5. Most clustering protocols assume homogeneous sensor capabilities. As renewable energy systems become more complex, the literature lacks robust solutions for heterogeneous networks involving sensors of varying energy, processing, and communication capacities.
6. While federated learning shows promise, few studies integrate real-time WSN data with predictive analytics, such as short-term solar irradiance forecasting or turbine failure prediction, to proactively optimize grid behavior.

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Conflict of interest

The authors have no competing interests to declare that are relevant to the content of this article.

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