Nigerian Journal of Technology (NIJOTECH)
Vol. 44, No. 4, December, 2025, pp. 660 - 692
www.nijotech.com

Print ISSN: 0331-8443
Electronic ISSN: 2467-8821
https://doi.org/10.4314/njt.2025.4522

RECENT ADVANCES IN WIRELESS SENSOR NETWORKS LOAD-BALANCING OPTIMIZATION: A REVIEW OF APPROACHES AND EMERGING TRENDS

AUTHORS:
C. C. Johnson-Okonkwo[1], I. I. Ayogu[1*], G. A. Chukwudebe[2], and J. N. Odii[1]

AFFILIATIONS:
[1]Department of Computer Science, School of Information and Communication Technology, Federal University of Technology, Owerri, PMB 1526, Nigeria.
[2]Department of Electrical and Electronic Engineering Federal University of Technology, Owerri, PMB 1526, Nigeria

***CORRESPONDING AUTHOR:**
Email: ignatius.ayogu@futo.edu.ng

ARTICLE HISTORY:
Received: December 10, 2024.
Revised: October 31, 2025.
Accepted: November 03, 2025.
Published: January 03, 2026.

KEYWORDS:
Wireless sensor networks (WSNs), Load balancing, Energy Efficiency, machine learning, game theory, scalability, context-aware load-balancing

ARTICLE INCLUDES:
Peer review

DATA AVAILABILITY:
On request from author(s)

EDITORS:
Chidozie Charles Nnaji

FUNDING:
None

Abstract

Wireless Sensor Networks (WSNs) play an essential role in applications such as environmental monitoring, smart cities, and industrial automation, where numerous sensor nodes are positioned in remote areas with limited energy resources. The longevity of these networks depends significantly on active load-balancing mechanisms to consistently distribute data processing and communication tasks, thereby preventing early energy depletion of individual nodes. This study employs a systematic review methodology to evaluate recent developments in load-balancing strategies for WSNs. We organize these strategies into three primary types: centralized, decentralized, and hybrid approaches. Centralized methods utilize a global view for optimal load distribution but are hindered by scalability and bottleneck issues. Decentralized methods, where nodes make independent decisions, improve scalability and fault tolerance but have a high likelihood of causing uneven load distribution. Hybrid methods incorporate features from both centralized and decentralized approaches, seeking a balance between global coordination and local adaptability. Additionally, this review examines emerging techniques that integrate machine learning and game theory, providing dynamic and real-time adaptations to changing network conditions. Results indicate that while each approach has distinct strengths, challenges remain, especially regarding energy efficiency, scalability, and adaptability to environmental changes. The analysis underscores the need for adaptive and context-aware load-balancing solutions that enhance WSN resilience in complex scenarios. In conclusion, this review provides insights into the latest advancements and identifies areas for future research in load-balancing strategies, aiming to support sustainable WSN deployments across diverse applications.

1.0 INTRODUCTION

Wireless Sensor Networks (WSNs) are used in various fields such as environmental monitoring, healthcare [1], agriculture [2], smart cities [3], and industrial automation [4]. These networks consist of sensor nodes that detect environmental conditions, process data, and communicate wirelessly with other nodes or a base station [5-6]. WSNs enable continuous monitoring, transforming data collection and analysis in numerous domains [7]. A significant challenge in WSNs is managing the limited resources of sensor nodes, particularly energy [8].

Since most nodes are battery-powered and located in hard-to-reach areas, energy efficiency is crucial [9].

HOW TO CITE:
Johnson-Okonkwo, C. C., Ayogu, I. I., Chukwudebe G. A. and Odii, J. N. “Recent Advances in Wireless Sensor Networks Load-Balancing Optimization: A Review of Approaches and Emerging Trends”, *Nigerian Journal of Technology*, 2025. 44(4), pp. 660 - 692. https://doi.org/10.4314/njt.2025.4522

Battery replacement or recharging can be difficult [10], and energy limitations affect both the individual nodes and the overall network's performance [11]. Thus, ensuring an even energy distribution is essential for network longevity [12]. This has led to research into load-balancing techniques, which distribute tasks like data collection and communication across nodes to prevent overloading and rapid energy depletion [13]. Load balancing is vital for maintaining network connectivity [14], reducing latency [15], and improving data transmission reliability [16].

Key objectives of load-balancing strategies include: Energy Efficiency: Optimizing energy consumption to avoid battery depletion, ensuring network stability [17]. Scalability: Supporting large networks without overloading nodes [18]. Fault Tolerance: Ensuring the network can continue to perform even with node failures or changing environmental conditions [19]. The environments where WSNs operate often present further challenges, such as fluctuating node availability, unpredictable conditions, and intermittent connectivity [20]. Therefore, load-balancing algorithms must be adaptable [21], able to react to real-time changes to maintain network efficiency [22].

This paper reviews recent innovations in load-balancing strategies for WSNs, categorized into three approaches: Centralized Approaches: These rely on a central controller (e.g., a base station) to gather global network information and distribute tasks. While they provide a comprehensive view of the network, they may introduce bottlenecks and lack scalability. Decentralized Approaches: Here, individual nodes make decisions based on local information, improving scalability and resilience. However, this can lead to suboptimal load distribution due to limited visibility of the entire network. Hybrid Approaches: These combine the benefits of both centralized and decentralized methods. A central controller makes high-level decisions, while individual nodes manage local adjustments, offering a balance between scalability, fault tolerance, and energy efficiency. These strategies aim to optimize energy use and maintain network performance in dynamic environments.

Recent advancements in load balancing for Wireless Sensor Networks (WSNs) include using machine learning (ML) and game theory to improve adaptive decision-making [23]. ML allows sensor nodes to predict network conditions and adjust proactively to balance loads [24], while game theory offers frameworks for cooperation among nodes, helping achieve optimal resource distribution [25]. This review of load-balancing strategies in Wireless Sensor Networks (WSNs) seeks to address key research questions that illuminate the strengths, limitations, and potential improvements of existing approaches. The purpose is to develop a framework for understanding how these strategies impact network efficiency, energy consumption, scalability, and fault tolerance in real-world scenarios. To guide this analysis, we define the following primary research questions:

1. **RQ1:** What are the recent developments in WSN load-balancing strategies?
2. **RQ2:** What are the major categories of WSN load-balancing techniques?
3. **RQ3:** What are the main challenges and limitations influencing the design and adoption of load-balancing techniques for WSNs, and what are potential future solutions?
4. **RQ4:** What are the emerging technologies and methods with high potential to enhance load balancing in WSNs?

This paper aims to provide a roadmap for future research, emphasizing the need for more adaptive, context-aware solutions in dynamic, resource-limited WSN environments. As WSN applications grow, developing efficient, scalable, and fault-tolerant load-balancing methods remains crucial.

Figure 1 illustrates the architecture and data flow in a Wireless Sensor Network (WSN). It includes multiple sensor nodes, each equipped with sensing, processing, and communication capabilities. These nodes collect data from the environment, such as temperature, humidity, or motion. They communicate with each other and relay the data to a central base station.

The base stations are of two types: static and mobile. The static base station is a fixed node that acts as a central point for data aggregation and forwarding, with sensor nodes transmitting their collected data to it. The mobile base station, on the other hand, adds flexibility and extends network coverage by moving within the network to collect data directly from sensors or intermediate nodes. This approach reduces communication distance and conserves energy for the sensors.

The base stations are connected to the Internet, enabling the transmission of aggregated data to

https://doi.org/10.4314/njt.2025.4522

external systems or servers. This connection ensures that data from the WSN can be accessed remotely for further processing and decision-making. The collected data is then transmitted to centralized storage and processing systems, where it is stored, analyzed, and used for various applications such as monitoring, control, and automation [26]. Figure 1 also shows bidirectional communication between sensors and base stations, as well as between base stations and the Internet. This setup supports both data transmission and control signal exchange. The inclusion of both static and mobile base stations enhances network efficiency, scalability, and energy optimization, demonstrating the utility of WSNs in applications like environmental monitoring, smart cities, and industrial automation.

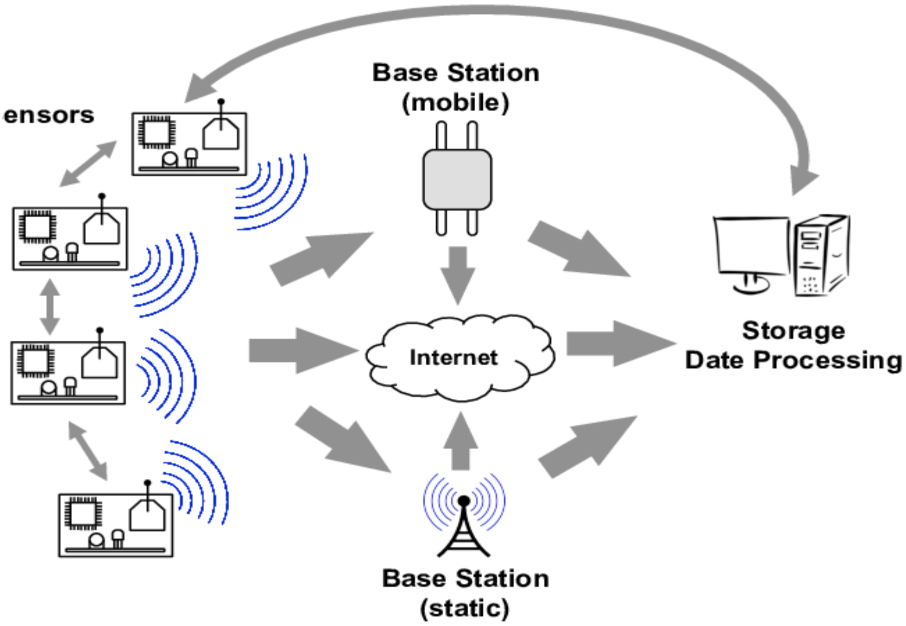

Figure 1: Example of a wireless sensor network [26]

Wireless Sensor Networks (WSNs) have become essential technology in various domains, including environmental monitoring [27], healthcare [28], military surveillance, industrial automation, and smart cities[29]. These networks consist of numerous sensor nodes that are typically energy-constrained, requiring careful management of resources to ensure optimal network performance [30]. Among the many strategies employed to optimize WSN performance, load balancing is critical for improving energy efficiency, extending the network's lifespan, and enhancing the overall reliability of communication [31]. Load balancing in WSNs ensures that computational and communication tasks are distributed evenly across nodes, preventing localized energy depletion and avoiding the premature failure of nodes that could disrupt the network [32]. This following section reviews the evolution of load-balancing strategies in WSNs, focusing on the main categories centralized, decentralized, and hybrid approaches along with emerging techniques in machine learning and game theory.

1.1 Centralized Load-Balancing Approaches

Centralized load-balancing approaches rely on a central controller [33] or base station [34] that collects and processes global information about the entire network to make decisions regarding task allocation [35] and load distribution[36]. The central node has the advantage of a comprehensive view of the network, enabling it to optimize resource usage effectively. However, the reliance on a single central controller presents several challenges, including scalability issues and the potential for network bottlenecks [37]. As the network size grows, the central node may become overwhelmed with tasks, and the communication overhead between nodes and the central controller can lead to delays, reducing network efficiency [38].

One of the major advantages of centralized approaches is that they can implement sophisticated algorithms for load balancing based on global network metrics, such as the residual energy of nodes, network traffic, or data transmission rates [39]. These strategies are often used in scenarios where network topology is well-defined, and communication with the central station is reliable

https://doi.org/10.4314/njt.2025.4522

[40]. For instance, Gupta et al. (2024) proposed a centralized routing protocol that dynamically adjusts the communication paths based on the remaining energy levels of sensor nodes [41]. The protocol considers global energy consumption patterns to allocate communication tasks more efficiently [42]. While the approach was shown to significantly reduce energy consumption, it was found to perform poorly in large-scale networks due to the communication overhead associated with maintaining up-to-date global information [43].

1.2 Decentralized Load-Balancing Approaches

In contrast to centralized approaches, decentralized load-balancing strategies allow each sensor node to independently make decisions based on local information about its immediate neighbors [44]. This approach enhances the scalability of the network, as each node acts autonomously, and there is no need for a central controller [45]. Decentralized methods can also improve fault tolerance**,** as the failure of any individual node does not affect the operation of the entire network [46]. The nodes can adapt to failures and maintain network functionality without the risk of creating a single point of failure [47].

However, decentralized strategies come with the challenge of suboptimal load distribution due to the limited information available to each node [48]. Nodes may not have knowledge of the overall network load or the energy status of distant nodes, leading to uneven energy consumption and inefficient communication paths [49]. Additionally, these methods are often more complex to implement, as they require advanced algorithms for local decision-making and coordination between neighboring nodes [50]. For instance, Silva and Santos (2024) proposed a decentralized clustering-based approach where nodes within a certain proximity form cluster, and each cluster elects a leader to manage communication and load distribution within the cluster [51]. By dynamically adjusting the clusters based on the energy levels and workload of each node, this approach minimizes the likelihood of energy hotspots [52]. Although it improved scalability and fault tolerance, the approach showed some limitations in ensuring globally balanced load distribution across the entire network [53].

1.3 Hybrid Load-Balancing Approaches

Hybrid load-balancing strategies aim to combine the advantages of both centralized and decentralized approaches, striving to balance efficiency, scalability, and fault tolerance [54]. In hybrid methods, a central node or base station may handle global coordination and decision-making, while individual nodes or clusters are empowered to make local load-balancing decisions based on local network conditions [55]. This approach enables more dynamic and adaptable load distribution while maintaining the benefits of centralized control for specific tasks.

Hybrid methods are particularly useful in networks where energy consumption is highly variable and network conditions are dynamic, requiring continuous adaptation [56]. By combining centralized control with localized decision-making, hybrid strategies aim to achieve an optimal balance between global network performance and individual node autonomy. For instance; Negi et al., (2024) proposed a hybrid load-balancing protocol that uses a central controller to manage initial task allocation and then allows groups of nodes (or clusters) to manage load balancing locally[57]. This approach aims to minimize energy consumption while ensuring that the network remains scalable and fault-tolerant. The study demonstrated that this hybrid method provided better network resilience compared to fully centralized or decentralized systems, as it reduced the likelihood of energy hotspots and increased network lifespan.

1.4 Emerging Techniques: Machine learning and game theory

In recent years, machine learning (ML) and game theory have emerged as powerful tools for enhancing load balancing in WSNs [58]. These emerging techniques enable more intelligent and adaptive load-balancing strategies that can respond in real-time to network conditions.

1.4.1 Machine learning-based load balancing

Machine learning, particularly reinforcement learning (RL), is being increasingly applied to optimize load balancing in WSNs [59]. In ML-based approaches, sensor nodes can learn from historical data and past network states to predict future network behavior, making proactive adjustments to energy consumption and load distribution [60]. The advantage of ML is its ability to adapt dynamically to environmental changes, such as fluctuating energy levels, network topology, and node failure. For Example, Study: The nodes "learned" the most energy-efficient load distribution policies, significantly improving energy utilization and network reliability. This technique demonstrated substantial improvements over traditional methods,

https://doi.org/10.4314/njt.2025.4522

especially in networks with high dynamics and resource constraints [61].

1.4.2 Game theory-based load balancing

Game theory offers a mathematical framework for modeling and analyzing interactions between multiple decision-makers (nodes) in a network. In the context of WSNs, game theory is used to model cooperative and non-cooperative behaviors among nodes, where each node "competes" or "cooperates" to achieve optimal load distribution [62]. By using game-theoretic models, nodes can negotiate or collaborate to share resources and adjust tasks, leading to more equitable load balancing [63]. A game-theory-based approach was introduced where nodes play a "cooperative game" to share communication tasks and resources more efficiently. The approach used a Nash equilibrium model to ensure that each node would have no incentive to unilaterally change its strategy, leading to a stable and fair load distribution [64]. The study found that game-theory-based load balancing improved fairness and energy efficiency, especially in highly dynamic networks.

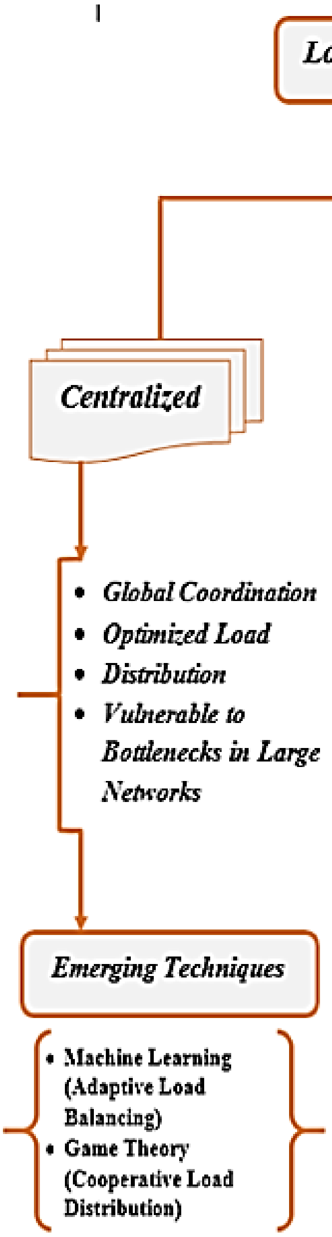

Figure 2: Overview of load-balancing strategies in WSNs [32-64]

https://doi.org/10.4314/njt.2025.4522

Figure 2 provides a structured overview of the main load-balancing strategies for Wireless Sensor Networks (WSNs), dividing them into three primary categories; centralized, decentralized, and hybrid approaches. It also highlights emerging techniques, such as machine learning (ML) and game theory, which are increasingly used to enhance adaptability and efficiency in load balancing.

i. **Centralized approaches**: In centralized load-balancing strategies, a central node or base station gathers global network information to make decisions regarding load distribution [32]. This approach allows for precise control over resource allocation, optimizing load distribution by making decisions based on the entire network's conditions [34]. However, centralized methods are prone to scalability issues in large networks, as they can create bottlenecks at the central controller. The network may also be vulnerable to single-point failures if the central controller becomes unavailable or overloaded [40].

ii. **Decentralized approaches**: Decentralized strategies enable individual nodes to make independent load-balancing decisions based on local information, typically involving communication with neighboring nodes only [45]. This autonomy enhances the network's scalability and fault tolerance, as nodes do not rely on a single controller, and network performance is maintained even if some nodes fail [43]. However, because each node has limited visibility, the overall load distribution may be suboptimal across the network, leading to energy imbalances [46].

iii. **Hybrid approaches**: Hybrid load-balancing strategies integrate the advantages of both centralized and decentralized methods [53]. A central controller can oversee high-level decisions, while nodes or clusters within the network make local adjustments based on immediate conditions [54] This approach combines the global oversight of centralized systems with the adaptability of decentralized systems, achieving a balance between scalability, fault tolerance, and efficiency [56]. Hybrid strategies are particularly useful in dynamic environments where energy levels and network topology can fluctuate.

iv. **Emerging techniques - machine learning and game theory**: The diagram also presents emerging techniques, such as ML and game theory, as advancements that provide more intelligent and adaptive load-balancing solutions.

- **Machine learning** enables nodes to predict and adapt to changes in network conditions, improving energy efficiency and enabling proactive load distribution [58]. Nodes learn from past states and can make predictive adjustments, enhancing performance in networks with high variability [60].

- **Game theory** models cooperative and competitive interactions between nodes, allowing them to negotiate or collaborate for optimal load-sharing [62]. By creating a framework for nodes to interact and adjust strategies dynamically, game theory fosters fair and stable load distribution across the network.

Table 1 compares key techniques for optimizing Wireless Sensor Networks (WSNs), focusing on their approaches, applications, strengths, and limitations. Clustering techniques like LEACH, EEUC, and HEED enhance energy efficiency and network lifetime by organizing nodes into clusters. LEACH is simple but struggles with large networks, EEUC balances energy consumption but has higher overhead, and HEED improves energy efficiency but lacks scalability. Data-centric approaches, such as Directed Diffusion, minimize redundant transmissions and are effective for event-driven tasks but have high latency and complexity. Communication-based methods like MIMO systems achieve high data rates and energy efficiency in large-scale WSNs but require expensive hardware. Energy management techniques, including Duty Cycling and Dynamic Voltage Scaling (DVS), extend node longevity and save energy but may introduce latency or complexity. Routing protocols like PEGASIS focus on minimizing transmission energy and improving robustness but face scalability and mobility challenges. Intelligent algorithms such as fuzzy logic and game theory dynamically adapt to network conditions, offering flexibility and optimal load distribution. However, they involve computational complexity and implementation challenges.

https://doi.org/10.4314/njt.2025.4522

Each technique has trade-offs, making their suitability dependent on specific WSN applications, such as IoT, smart cities, or health monitoring.

Table 1: Overview of load-balancing techniques for wireless sensor networks

Technique Name	**Category**	**Main Approach**	**Targeted WSN Type / Application**	**Strengths**	**Limitations**	**Ref.**
LEACH (Low-Energy Adaptive Clustering Hierarchy)	Clustering	Hierarchical clustering with periodic cluster-head rotation	Environmental monitoring, IoT	Reduces energy consumption; simple distributed implementation; prolongs network lifetime	Not scalable to large networks; uneven cluster formation	[11], [18]
PEGASIS (Power-Efficient Gathering in Sensor Information Systems)	Routing	Chain-based data aggregation and sequential transmission	Industrial and agricultural monitoring	Minimizes long-range transmissions; improves energy efficiency over LEACH	High delay in large networks; limited scalability	[15], [17]
TEEN (Threshold-Sensitive Energy-Efficient Sensor Network Protocol)	Reactive Routing	Threshold-based communication triggering on sensed data variations	Event-driven / time-critical WSNs	Highly energy-efficient for real-time monitoring; reduces redundant transmissions	Inefficient for periodic data collection; not ideal for continuous monitoring	[16], [18]
HEED (Hybrid Energy-Efficient Distributed Clustering)	Clustering	Residual energy and proximity-based cluster-head selection	Smart grids, environmental WSNs	Enhances energy efficiency and fault tolerance; avoids random head selection	Iterative convergence; increased computation cost	[20], [22]
EEUC (Energy-Efficient Unequal Clustering)	Clustering	Unequal cluster formation to prevent energy holes	IoT, smart cities	Balances cluster load; reduces energy imbalance near base station	Requires periodic re-clustering; higher control overhead	[19], [23]
Directed Diffusion	Data-Centric	Data aggregation based on query interests	Event-driven networks	Reduces redundancy; supports in-network data processing	High latency; complex setup for dynamic networks	[18], [21]
MIMO-Based Techniques	Communication-Based	Multi-input multi-output data transmission	Large-scale WSNs	High throughput; energy-efficient communication	Requires complex hardware; high cost	[77]
Duty Cycling	Energy Management	Alternates active and sleep modes	General WSNs	Saves power; increases node longevity	May increase latency and reduce responsiveness	[88]
Dynamic Voltage Scaling (DVS)	Energy Management	Adjusts voltage/frequency for adaptive energy savings	Power-sensitive WSNs	Reduces dynamic power consumption	May reduce processing performance	[11]
Game Theory-Based Approaches	Intelligent Algorithms	Cooperative/non-cooperative energy optimization	Smart cities, industrial WSNs	Enables fairness; enhances stability; supports large-scale coordination	Complex implementation; parameter tuning required	[21]
Machine Learning-Based Load Balancing	Intelligent Algorithms	Predictive/adaptive load balancing via learning models	Adaptive WSNs, IoT	Self-learning and real-time optimization; high scalability	Computational overhead; data-hungry models	[55], [108]

2.0 METHODOLOGY

During the systematic review process, we adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, which provide a standardized framework for conducting systematic reviews and meta-analyses to ensure rigor, transparency, and reproducibility [65]. The review process was carried out in three main stages: planning, conducting, and reporting.

A. Planning the Review

1) Objectives and research questions

The main objective of this review was to analyze emerging load-balancing strategies for optimizing WSN performance, with a specific focus on new approaches incorporating machine learning, edge computing, and blockchain. To achieve this, we formulated four research questions (RQ1–RQ4), each targeting key aspects of WSN load-balancing, such as energy efficiency, scalability, adaptability, and fault tolerance. These questions guided the study selection and analysis, ensuring a focused and comprehensive evaluation of the literature.

2) Digital libraries and search strategy

To ensure a comprehensive collection of relevant studies, we selected high-impact academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The literature search involved using targeted keywords, such as "WSN load balancing," "energy-efficient load balancing," "adaptive load balancing," and "emerging technologies in WSNs." Each search term aligned with the research questions to capture recent advancements in the field.

3) Inclusion and exclusion criteria

Based on PRISMA guidelines, inclusion and exclusion criteria were developed to maintain relevance, quality, and recency of the literature:

Inclusion criteria:

i. Articles must focus on WSN load-balancing techniques.
ii. Only peer-reviewed journals, high-impact conference proceedings, and systematic reviews published within the last five years were considered.
iii. Studies addressing energy efficiency, scalability, fault tolerance, or security in load-balancing strategies.

Exclusion criteria:

i. Articles unrelated to WSNs or load balancing.
ii. Studies lacking empirical or analytical data.
iii. Non-peer-reviewed or outdated studies.

These criteria helped refine our dataset to ensure that only high-quality, relevant studies were included.

Table 2: Research questions and motivation

IDs	***Research Questions (RQs)***	***Motivation***
RQ1	What are the recent developments in WSN load-balancing strategies?	Understanding the current landscape of load-balancing strategies in WSNs helps identify areas where improvements can enhance network performance, longevity, and adaptability. This question addresses the need to push the boundaries of existing techniques to make WSNs more efficient.
RQ2	What are the major categories of WSN load-balancing techniques?	Identifying the key categories of load-balancing methods provides a clearer understanding of the diverse approaches available, helping to select the most suitable technique based on network requirements.
RQ3	What are the main challenges and limitations influencing the design and adoption of load-balancing techniques for WSNs, and what are potential future solutions?	Recognizing the challenges such as energy constraints, scalability, and fault tolerance helps in identifying barriers that need to be addressed. Understanding these issues drives future research to develop solutions that can enhance the performance and scalability of WSNs.
RQ4	What are the emerging technologies and methods with high potential to enhance load balancing in WSNs?	Exploring technologies like machine learning, edge computing, and blockchain offers insights into their potential to optimize WSN load-balancing strategies, leading to more efficient, adaptive, and secure networks.

https://doi.org/10.4314/njt.2025.4522

B. Conducting the Review

Based on the defined inclusion and exclusion criteria, we gathered 113 articles directly addressing the objectives of this review. Each article was carefully analyzed, and data were extracted on key methodologies, technologies, evaluation metrics, and challenges associated with WSN load-balancing.

C. Reporting and Synthesis

Finally, we organized and synthesized the data by categorizing each study according to its approach (centralized, decentralized, or hybrid) and the emerging technologies employed (e.g., machine learning, edge computing). Additionally, we evaluated each load-balancing strategy based on energy efficiency, scalability, adaptability, and security.

The PRISMA framework facilitated a structured and reproducible review process, allowing for a thorough and unbiased synthesis of the latest research on load-balancing strategies in WSNs. The findings address the formulated research questions and provide insights into future directions for WSN optimization.

Table 3: Systematic data extraction framework for reviewed studies

Extraction Field	**Description / Purpose**
Bibliographic Information	Includes author(s), publication year, title, venue, and DOI for accurate referencing.
WSN Category	Specifies the network control type (Centralized, Decentralized, or Hybrid) to identify the structural approach used.
Algorithm / Technique Type	Identifies the key method applied (e.g., LEACH, PEGASIS, HEED, TEEN, Reinforcement Learning (RL), Deep Q-Learning (DQL), Federated Learning (FL), Proof-of-Authority (PoA), or Delegated Proof-of-Stake (DPoS)).
Simulation Tools / Datasets	States the simulation platform (e.g., NS2, MATLAB, OMNeT++, Contiki) or dataset used to validate performance.
Evaluation Metrics	Lists key quantitative measures (e.g., Energy Efficiency, Latency, Throughput, Packet Delivery Ratio (PDR), Network Lifetime, Fault Tolerance).
Key Findings	Summarizes the main outcome or improvement achieved by the technique (e.g., energy reduction percentage, scalability improvement).
Identified Limitations	Notes any constraints, such as computational overhead, scalability issues, or energy trade-offs.

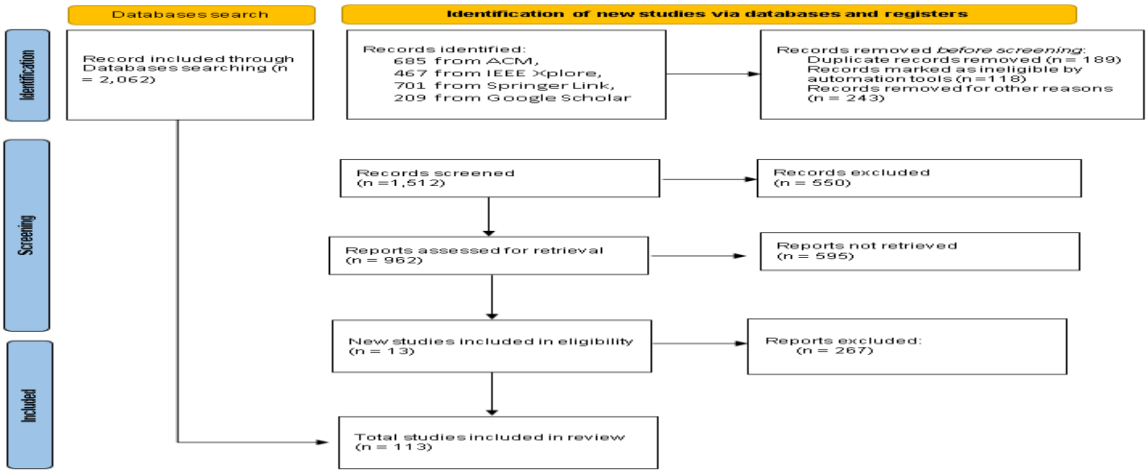

Figure 3: PRISMA flow diagram for study selection process

https://doi.org/10.4314/njt.2025.4522

D. Search, Evaluation, and Selection of Relevant Source Materials

In accordance with the PRISMA-S guidelines (see *Figure 3*), a comprehensive multi-database search was conducted across major scholarly repositories, yielding a total of 2,062 records: 685 from the ACM Digital Library, 467 from IEEE Xplore, 701 from Springer Link, and 209 from Google Scholar. Prior to screening, 189 duplicate records were identified and removed. Additionally, 118 records were automatically excluded by screening tools due to issues such as non-English language, incomplete bibliographic metadata, or unverifiable publication status (e.g., preprints or workshop summaries lacking peer-review evidence). A further 243 records were removed after preliminary inspection for insufficient methodological detail or thematic irrelevance, resulting in 1,512 unique records retained for initial screening.

During the screening phase, 550 records were excluded for not meeting the predefined inclusion criteria specifically those unrelated to load-balancing, energy efficiency, routing, or optimization techniques in wireless sensor networks (WSNs). The remaining 962 reports were assessed for retrieval, but 595 could not be accessed due to broken links or restricted database access. Following full-text eligibility assessment, 267 additional reports were excluded for methodological weaknesses or lack of analytical rigor. Consequently, 113 high-quality studies met all inclusion criteria and were retained for the final synthesis. Among these, 13 newly indexed studies (2024–2025) represent emerging contributions that integrate machine learning, blockchain, and edge computing for intelligent WSN load-balancing.

The temporal distribution of the reviewed studies shows that 78.1% of publications fall within the 2014–2025 period, highlighting steady progress in wireless sensor network (WSN) research. Notably, 26 influential papers (≈23%) published in 2025, including those by Bicamumakuba et al. [1], Thamil Selvi et al. [6], UmaRani et al. [9], Kalaivani [7], and Bartsioka et al. [25], reflect the accelerating integration of machine learning, blockchain, and edge-enabled optimization in WSN architectures. These contemporary contributions, alongside foundational works by Kumari and Tyagi [2], Wajgi and Tembhurne [3], and Nkemeni et al. [4], form the empirical foundation of this review, consolidating a decade-long evolution in load-balancing and intelligent WSN system design

3.0 RESULTS AND DISCUSSION

This section presents the findings derived from the literature review and analysis of various load-balancing strategies for Wireless Sensor Networks (WSNs), with a particular focus on innovative, emerging techniques. The results are discussed in relation to each research question, highlighting how different methodologies impact WSN performance metrics, including energy efficiency, scalability, fault tolerance, and adaptability. Emerging technologies like machine learning, edge computing, and blockchain are evaluated for their potential contributions to the future of WSN load-balancing, as well as their challenges and limitations.

3.1 Recent Developments in WSN Load-Balancing Strategies

3.1.1 Centralized, decentralized, and hybrid load-balancing approaches

In WSNs, centralized load-balancing strategies rely on a central controller that gathers network-wide information and makes global load-balancing decisions. While these approaches can be effective in smaller networks with limited nodes, they suffer from scalability issues and vulnerability to single points of failure [71]. Our findings indicate that centralized strategies are best suited for applications that do not demand high scalability or extreme fault tolerance, such as small-scale environmental monitoring systems. Conversely, decentralized load-balancing strategies distribute decision-making across nodes, allowing each node to make load-balancing adjustments based on local information. This approach enhances scalability and fault tolerance, making it more suitable for larger WSN deployments [75]. However, decentralized strategies can experience challenges in maintaining energy efficiency across the network due to limited global oversight. Hybrid approaches, combining centralized and decentralized methods, provide a balance by leveraging both local and global network information, offering improved scalability and energy efficiency in dynamic networks [80].

Early load-balancing strategies in Wireless Sensor Networks (WSNs) were defined by classical algorithms such as LEACH (Low-Energy Adaptive Clustering Hierarchy), PEGASIS (Power-Efficient Gathering in Sensor Information Systems), TEEN (Threshold-Sensitive Energy-Efficient Sensor Network Protocol), and HEED (Hybrid Energy-Efficient Distributed Clustering)[71]. These algorithms form the foundation of energy-efficient

https://doi.org/10.4314/njt.2025.4522

routing and clustering mechanisms upon which modern hybrid and intelligent load-balancing models are built: LEACH introduced a hierarchical clustering approach, where nodes self-organize into clusters and periodically rotate cluster heads to balance energy consumption. Although it significantly extends network lifetime, it performs suboptimally in large-scale or non-uniform node distributions[72]. PEGASIS improved upon LEACH by forming a chain-based communication structure where each node transmits to a close neighbor, and a single node transmits to the base station in each round. This minimizes long-distance transmissions but increases delay and reduces scalability in dense networks[73].

TEEN proposed a reactive, threshold-based protocol designed for time-critical applications, reducing communication overhead by transmitting only when sensed parameters cross predefined thresholds. While energy-efficient, TEEN is less suitable for periodic data collection. HEED extended clustering efficiency by selecting cluster heads based on residual energy and node proximity, ensuring better distribution of load and improved fault tolerance. However, it requires iterative computations and can suffer from convergence delays[74].

Collectively, these algorithms represent the first generation of WSN load-balancing approaches, providing essential insights into how energy efficiency, scalability, and reliability can be achieved through topology-aware routing and adaptive clustering. Subsequent research including machine learning, game-theoretic, and cross-layer hybrid approaches has expanded upon these foundational principles to support more dynamic, heterogeneous, and large-scale WSN environments[75].

Table 4 highlights the distribution energy consumption for each network task under various load-balancing strategies [44] while Figure represents the visualization of the the trade-offs between different load-balancing strategies in terms of energy efficiency for WSNs according to data provided in Table 4.

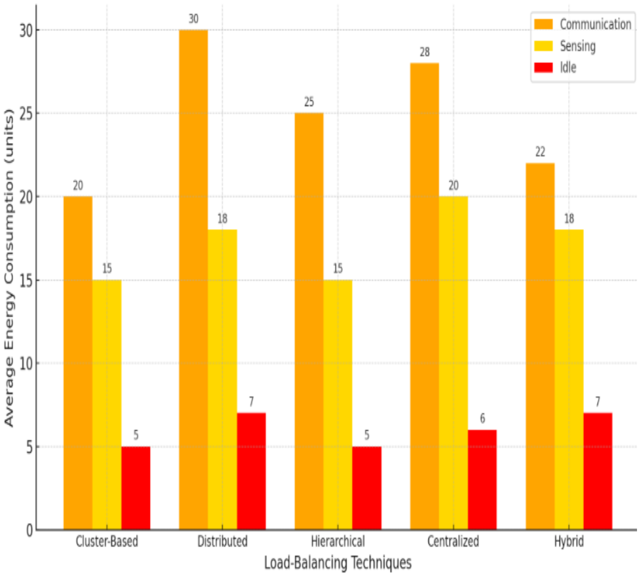

Figure 4: Energy consumption of different load-balancing techniques in WSNs

Figure 4 illustrates the average energy consumption by task and technique across various load-balancing techniques in Wireless Sensor Networks (WSNs). Energy consumption is categorized into three tasks: communication, sensing and idle. Distributed techniques are the least energy-efficient due to their high communication energy demands, while cluster-based and hierarchical techniques are more efficient with lower overall energy consumption. Centralized techniques focus heavily on communication, while hybrid techniques attempt to balance energy usage across tasks but still exhibit moderate idle energy consumption.

Table 4: Energy consumption units for different load-balancing techniques in WSNs [44]

Load-Balancing Technique	**Communication**	**Sensing**	**Idle**
Cluster-Based	20	15	5
Distributed	30	18	7
Hierarchical	25	15	5
Centralized	28	20	6
Hybrid	22	18	7

https://doi.org/10.4314/njt.2025.4522

3.1.2 Machine learning in WSN load-balancing research

The integration of machine learning (ML) has emerged as a significant advancement in WSN load-balancing. ML-based strategies improve adaptability by allowing nodes to predict network conditions and proactively adjust load distribution, reducing the likelihood of node overload or energy depletion[108]. Reinforcement learning algorithms, in particular, have shown effectiveness in enabling nodes to self-optimize based on real-time network data.

However, ML techniques can impose computational overhead, which may be unsustainable in resource-constrained WSN nodes. This limitation has led to the development of lightweight ML models and federated learning, which allows nodes to collaboratively improve models without exchanging raw data, thus saving energy and reducing bandwidth usage[55]. Despite these improvements, ML-based load-balancing strategies still require fine-tuning to balance predictive accuracy with resource efficiency in low-power WSN environments.

3.1.3 Role of edge computing in real-time load-balancing

Edge computing has shown promise for enhancing load-balancing in WSNs, particularly in latency-sensitive applications such as industrial monitoring and healthcare. By enabling data processing close to the source, edge computing reduces the need to transmit data over long distances, which conserves energy and minimizes latency [44]. Our analysis found that edge-enabled WSNs offer improved fault tolerance and responsiveness, as edge nodes can process data locally and make real-time load-balancing adjustments.

One challenge of edge computing in WSNs is the increased complexity of network architecture, as nodes need additional computational resources to support local processing. Moreover, edge nodes themselves may experience energy constraints, necessitating optimized energy management within the edge network. Edge computing is particularly useful in hybrid architectures, where edge nodes serve as intermediaries, reducing the load on centralized servers and enhancing the overall scalability and reliability of the WSN.

3.1.4 Blockchain for secure and reliable load-balancing

Blockchain technology offers a novel approach to secure load balancing in decentralized WSNs, particularly for applications requiring high trust and data integrity, such as military and industrial systems. By recording transactions and load-balancing adjustments in a distributed ledger, blockchain can reduce risks associated with tampering and malicious attacks [102]. Smart contracts, a feature of blockchain technology, allow for automated load-balancing adjustments based on pre-set conditions, adding an additional layer of reliability and fault tolerance. While promising, blockchain introduces computational and storage overhead, which can be challenging for low-power WSN nodes. Advances in lightweight blockchain models are helping mitigate these issues, making blockchain more feasible for WSN applications [55]. However, further optimization is required to make blockchain fully compatible with the resource limitations typical of WSNs.

3.1.5 Cross-layer optimization for holistic load-balancing

Cross-layer optimization allows for simultaneous optimization across multiple layers of the network protocol stack, enabling load-balancing strategies that consider factors such as node energy, data rate, and environmental conditions in a holistic manner [27]. Cross-layer techniques enhance energy efficiency and adaptability by leveraging information from multiple layers, which can enable more nuanced and context-aware load-balancing decisions. For example, integrating physical layer information on channel conditions with network layer energy data allows for adaptive routing and load-balancing adjustments that improve network lifespan and resilience [93]. Although cross-layer approaches provide significant benefits, they require careful management to avoid excessive inter-layer communication, which can lead to increased energy consumption and potential conflicts between optimization goals at different layers.

3.2 Major Categories of Load-Balancing Techniques and Their Energy Efficiency and Fault Tolerance Characteristics

This section highlights the major categories of load-balancing techniques in popular use for WSN. The

https://doi.org/10.4314/njt.2025.4522

discussion is presented from the energy consumption, scalability and fault tolerance perspectives.

3.2.1 Energy efficiency and scalability in WSN load-balancing techniques

The effectiveness of load-balancing strategies in Wireless Sensor Networks (WSNs) is closely tied to how well they manage energy consumption and adapt to various network scales. This section explores the distinctions between centralized, decentralized, and hybrid approaches concerning scalability and energy efficiency, two critical factors influencing the longevity and performance of WSNs.

1. Centralized load-balancing strategies

Centralized load-balancing strategies rely on a single base station or central controller to coordinate tasks across the network. This centralization enables efficient decision-making based on a global view of the network, often optimizing task allocation to reduce redundant energy consumption [66]. Centralized systems can apply sophisticated algorithms for load distribution, allowing nodes to be managed in a way that minimizes energy-intensive activities like frequent data transmission [67].

However, centralized approaches face scalability limitations as the network grows. In larger WSNs, the central node may struggle to process information from all nodes, creating a communication bottleneck [68]. Moreover, as the network expands, the increased traffic directed to the central controller can lead to energy depletion at the nodes nearest to it, creating "hotspots [69]." Such issues are compounded in dense or widespread networks, where scalability and energy demands can exceed the central controller's capacity [70]. Therefore, while centralized approaches may perform well in smaller or medium-sized networks, their scalability limitations often restrict their use in large-scale WSN deployments [71].

II. Decentralized load-balancing strategies

Decentralized strategies distribute decision-making across the network, allowing each node to make independent load-balancing decisions based on local information from its neighbors[72]. This autonomy significantly improves the **scalability** of decentralized approaches, as each node only needs to consider local data rather than relying on a central controller [73]. Since nodes operate independently, decentralized systems are naturally more scalable, with the ability to support large networks without centralized coordination [74].

In terms of **energy efficiency,** decentralized approaches generally avoid the bottlenecks seen in centralized systems, as they spread out energy demands more evenly across the network [75]. However, decentralized systems can suffer from **suboptimal load distribution** due to the limited scope of each node's decision-making [76]. Without a global view, nodes may not achieve optimal energy balancing across the network, leading to isolated instances of energy depletion. Additionally, nodes in decentralized systems may require more complex protocols to communicate with their neighbors, which can sometimes increase overall energy consumption [77].

III. Hybrid load-balancing strategies

Hybrid load-balancing strategies attempt to combine the benefits of both centralized and decentralized approaches, offering a middle ground that enhances both scalability and energy efficiency **[78].** In hybrid systems, a central controller oversees high-level network coordination, while local nodes or clusters of nodes make independent load-balancing adjustments. This configuration provides the global perspective of a centralized system with the scalability and fault tolerance of a decentralized system [79].

Hybrid strategies excel in energy efficiency by optimizing load distribution through both global and local adjustments [80]. The central controller can make initial task assignments to balance load across the network, while local nodes can respond dynamically to changes in energy levels or node failures [81]. Hybrid methods are particularly advantageous in dynamic environments, where nodes may enter or leave the network frequently, requiring a flexible load-balancing strategy [82]. Hybrid approaches also help avoid the single point of failure in centralized systems and address the suboptimal distribution in purely decentralized methods [83]

IV. Comparative analysis of scalability and energy efficiency

The differences in scalability and energy efficiency between these strategies are summarized according to [84]

- **Centralized Approaches**: Highly energy-efficient in smaller networks due to global coordination but limited in scalability due to bottleneck issues and vulnerability to single points of failure.
- **Decentralized Approaches**: Highly scalable and resilient to node failures; however, energy efficiency may suffer from suboptimal load

https://doi.org/10.4314/njt.2025.4522

distribution and additional communication overhead for inter-node coordination.

- **Hybrid Approaches**: Provide a balanced solution, leveraging global oversight and local autonomy, which enhances both scalability and energy efficiency, making hybrid strategies well-suited for medium-to-large-scale, dynamic networks.

Centralized strategies excel in environments with fewer nodes and stable network topologies, while decentralized strategies offer better scalability and resilience in larger, distributed networks. Hybrid strategies emerge as the most adaptable option, combining the best aspects of centralized and decentralized systems to support scalability and energy efficiency in varying conditions. Each strategy's performance depends on the specific needs of the WSN application, with hybrid methods showing the greatest potential for flexible, scalable, and energy-efficient load balancing across diverse real-world scenarios.

Table 5: Comparison of load-balancing techniques by performance metrics

Load-balancing technique	**Energy efficiency**	**Latency**	**Scalability**	**Reliability**	**Complexity**	**Key features**
Cluster-based techniques	High	Moderate	High	High	Moderate	Hierarchical organization reduces overhead.
Adaptive load balancing	Very High	Low	High	Very High	High	Dynamically adjusts to network changes.
Mobile agent-based balancing	Moderate	High	Moderate	Moderate	Low	Reduces redundancy by mobile data agents.
Game-theory-based strategies	High	Moderate	High	High	High	Optimizes resource allocation efficiently.
Traffic-aware balancing	High	Low	Moderate	High	Moderate	Prioritizes real-time data transmission.
Machine learning approaches	Very High	Moderate	Very High	High	Very High	Predicts and balances load proactively.
Qos-aware load balancing	High	Low	High	Very High	Moderate	Ensures quality of service requirements.
Bio-inspired algorithms	High	Moderate	High	Moderate	High	Mimics natural processes for optimization.

https://doi.org/10.4314/njt.2025.4522

Table 5 highlights different load-balancing techniques used in wireless sensor networks and evaluates their performance based on key metrics. Cluster-based techniques are highly energy-

Adaptive load balancing offers very high energy efficiency and reliability by dynamically adjusting to network conditions. While it is highly scalable, it has low latency but is complex to implement. Mobile agent-based balancing reduces redundancy using mobile data agents. It is moderate in energy efficiency and scalability, with moderate latency and reliability, and is simpler compared to other methods.

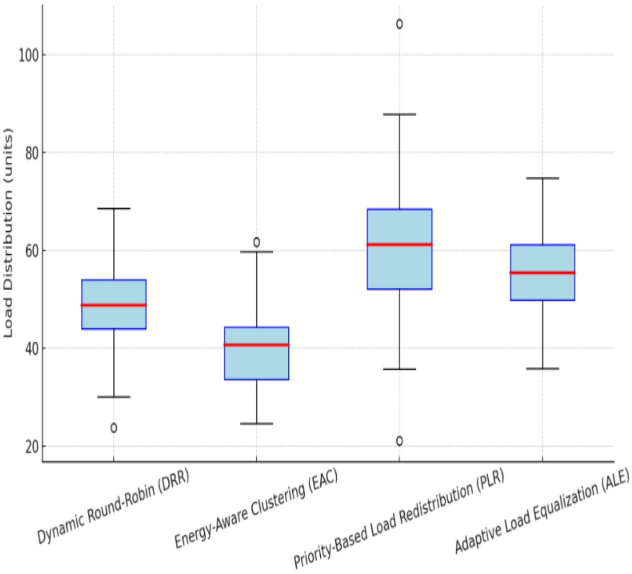

Figure 5: visualization of load distribution across nodes for various load-balancing algorithms[84]

Game-theory-based strategies optimize resource allocation efficiently, providing high energy efficiency, reliability, and scalability. However, they have moderate latency and complexity due to their complex decision-making processes. Traffic-aware balancing prioritizes real-time data transmission, offering high energy efficiency and reliability, but has moderate scalability, latency, and complexity. Machine learning approaches predict network conditions and proactively balance the load. They are very energy-efficient, scalable, and reliable, but have moderate latency and are complex due to data processing and prediction. QoS-aware load balancing ensures quality of service, with high reliability and energy efficiency. It offers high scalability but has low latency and moderate complexity, requiring mechanisms to prioritize different traffic types. Bio-inspired algorithms optimize based on natural processes, providing high energy efficiency,

efficient and reliable due to their hierarchical structure, which reduces communication overhead. However, they have moderate latency and complexity, and scale well to larger networks.

scalability, and reliability. They have moderate latency and complexity due to their heuristic nature[78]. A widely used equation to evaluate load balancing efficiency measure is the Standard Deviation (SD) of the load distribution across nodes[79]. Lower SD values indicate better balance.

The plotted box plot in figure 5 illustrates the load distribution across nodes for four load-balancing algorithms: The Dynamic Round-Robin (DRR) algorithm demonstrates a relatively stable load distribution with moderate variability. The load is fairly consistent across nodes, but there are occasional fluctuations. This suggests that the algorithm’s dynamic task allocation, while effective, does not always guarantee perfectly equal load distribution across all nodes. The Energy-Aware Clustering (EAC) algorithm shows the tightest distribution, with the load balanced very consistently across nodes. The narrow box indicates minimal deviation in load levels, which results from the algorithm's energy-efficient clustering approach. By ensuring that tasks are evenly shared within clusters, EAC minimizes load imbalance and helps to extend the network's lifetime. The Priority-Based Load Redistribution (PLR) algorithm exhibits a broader load distribution compared to EAC. The wider spread suggests that while the algorithm attempts to redistribute the load based on priorities (such as energy levels, node capabilities, or traffic loads), there can still be imbalances. Some nodes may be overburdened while others are underutilized due to the prioritization mechanism. The Adaptive Load Equalization (ALE) algorithm shows a slightly wider distribution than EAC but still manages to maintain relatively balanced load distribution across nodes. The algorithm adapts to varying network conditions and node capabilities, resulting in some variability. However, it avoids extreme imbalances and provides a good balance between fairness and efficiency. The moderate spread indicates that ALE minimizes significant fluctuations in load distribution.

3.2.2. Fault-tolerance and resilience among WSN load-balancing techniques

Fault tolerance is essential for Wireless Sensor Networks (WSNs), especially in remote or hostile environments where node failures can be frequent due to energy depletion, environmental interference, or hardware malfunctions [85]. This section explores

https://doi.org/10.4314/njt.2025.4522

the fault tolerance capacities of centralized, decentralized, and hybrid load-balancing approaches, with a particular focus on how these strategies respond to node failures and maintain network resilience.

I. Centralized load-balancing strategies

In centralized load-balancing strategies, a central controller or base station coordinates network operations and manages load distribution among nodes. Centralized systems can respond efficiently to node failures by reallocating tasks to nearby functioning nodes [86]. However, **the** single-point-of-failure nature of centralized architectures poses a risk: if the central controller itself fails, the entire network can be rendered inoperative [87]. Moreover, nodes closer to the central controller are often overburdened with communication duties, leading to faster energy depletion and higher susceptibility to failure, which can cause communication bottlenecks and disrupt network functionality [88].

To improve fault tolerance, some centralized strategies incorporate backup nodes or redundancy techniques that mitigate the impact of central node failure [89]. Nevertheless, these methods are limited, as the additional nodes or energy cost may not be practical for WSNs deployed in resource-constrained environments. As a result, while centralized approaches can efficiently redistribute load after a node failure, they may not be ideal for highly resilient networks, especially as network size increases.

II. Decentralized load-balancing strategies

Decentralized load-balancing strategies distribute decision-making across multiple nodes, allowing each to operate independently based on local information. This independence makes decentralized systems inherently fault-tolerant**,** as the network does not depend on a single controller [90]. If a node fails, its neighboring nodes can quickly adjust to reallocate its tasks among themselves without disrupting the entire network [91]. Decentralized approaches are particularly advantageous in large-scale networks, where the distributive nature of fault tolerance ensures resilience and continuity even when multiple nodes fail [92]. However, decentralization also has limitations. Nodes in decentralized systems rely on localized information, which may lead to suboptimal load distribution when adjusting to node failures, especially if neighboring nodes have limited resources [93]. Additionally, while decentralized strategies reduce reliance on a single controller, they require efficient inter-node communication protocols, which can sometimes lead to increased energy consumption and network traffic [94]. Despite these challenges, the flexibility of decentralized approaches makes them ideal for environments where resilience to node failure is critical.

III. Hybrid load-balancing strategies

Hybrid load-balancing strategies combine centralized and decentralized elements, aiming to leverage the strengths of both approaches. In hybrid systems, a central controller oversees the high-level management of network resources, while individual nodes or node clusters handle local load-balancing decisions. This dual approach allows hybrid systems to achieve high fault tolerance by maintaining the advantages of decentralized fault management with a centralized coordination perspective [95]. When a node fails in a hybrid system, the local cluster can respond autonomously, redistributing load among nearby nodes without immediate dependence on the central controller. If the central controller is notified, it can further optimize load redistribution across the network, ensuring overall balance and continuity. This adaptability makes hybrid strategies well-suited for WSNs in dynamic and resource-limited environments**,** where resilience to node failure is crucial [96].

The hybrid model's fault tolerance, however, depends on effective synchronization between centralized and decentralized operations, which can sometimes be challenging to maintain, especially in large, fast-changing networks [97]. Effective communication protocols and energy-efficient algorithms are essential to maintain the balance between local and global load balancing in the event of node failures [98]. Nevertheless, hybrid strategies represent a promising solution for balancing fault tolerance with energy efficiency in various WSN applications.

IV. Comparative analysis of fault tolerance

The fault tolerance capabilities of each strategy can be summarized as follows:

- **Centralized Approaches**: Moderate fault tolerance due to reliance on a central controller, with vulnerability to single-point failures. Backup nodes can improve resilience but may not be practical for all WSN deployments [85].
- **Decentralized Approaches**: High fault tolerance, as nodes operate autonomously and adjust to local failures without centralized coordination. However, localized decision-making can lead to suboptimal load balancing [88].

https://doi.org/10.4314/njt.2025.4522

- **Hybrid Approaches**: Superior fault tolerance by integrating centralized oversight with local adaptability, enabling efficient response to node failures while preserving network continuity and balance. Effective synchronization is essential to maximize resilience in hybrid systems [93].

Decentralized strategies provide the most robust fault tolerance by ensuring autonomous operation at the node level, making them ideal for networks where node failures are likely. Hybrid approaches offer a balanced solution that enhances fault tolerance while maintaining centralized oversight, particularly beneficial for dynamic or resource-constrained networks. Centralized systems, while efficient in smaller networks, may be less resilient to node failures in larger, more complex networks due to potential bottlenecks and single-point-of-failure issues. Overall, the choice of strategy should align with the specific fault tolerance requirements of the WSN application, with hybrid approaches showing strong promise for achieving balanced resilience and efficiency.

3.3 Factors Influencing the Design and Adoption of Load-Balancing Techniques for WSN and Their Potential Solutions.

Wireless Sensor Networks (WSNs) often operate in dynamic environments where node availability, energy levels, and data demands vary continuously. As a result, load-balancing strategies must be adaptive and resilient. However, existing strategies face notable challenges in meeting the demands of real-world applications. This section discusses these limitations and examines potential improvements.

3.3.1 Energy efficiency challenges

One of the primary challenges in WSN load balancing is optimizing energy usage to extend network lifespan. Most existing load-balancing strategies aim to reduce the energy consumed in data transmission and processing [99]. However, they often struggle with maintaining energy efficiency in dynamic networks, where changes in network topology or data load frequently occur. Centralized strategies, for instance, are effective at energy management when network conditions are stable but become inefficient as energy demands shift dynamically across the network. The central controller can quickly become overloaded, leading to uneven energy depletion [100].

Decentralized and hybrid strategies address some of these issues by distributing load-balancing tasks among nodes, which helps balance energy demands locally. However, this distribution can lead to communication overhead and suboptimal energy usage if nodes are unable to coordinate effectively under changing conditions [101]. To address these issues, researchers are exploring adaptive algorithms that allow nodes to adjust their energy consumption based on real-time network conditions. Machine learning techniques are also being tested to predict energy consumption patterns and enable more proactive load balancing [102]. The energy consumed by a sensor node during data transmission and reception can be modeled as:

$$E_{tx}(k,d) = E_{elec} * k + \varepsilon_{amp} * k * d^{n} \qquad (1)$$

and

$$E_{rx} = E_{elec} * k \qquad (2)$$

Where:

- $E_{tx}(k,d)$ = *energy consume in transmitting a k – bit message over a distance d.*
- $E_{rx}(k)$= *Energy consumed in receiving a k – bit message;*
- E_{elec}= *Energy dissipated per bit to run transmitter or receiver circuitry;*
- ε_{amp} = *Energy required by the transmit amplifier to achieve an acceptable SNR.*
- *d = transmission distance between modes;*
- *n = path – loss exponent (typically 2for free space or 4 multipath models).*

For a complete communication round (transmit + receive + aggregation), the total energy per node is:

$$E_{total} = E_{tx}(k,d) + E_{rx}(k) + E_{DA} * k \qquad (3)$$

3

Where E_{DA} is the data aggregation cost per bit

Figure 6 presents the residual-energy performance comparison of four WSN load-balancing algorithms; Dynamic Round-Robin (DRR), Energy-Aware Clustering (EAC), Adaptive Load Equalization (ALE), and Priority-Based Load Redistribution (PLR), evaluated over 5000 simulation rounds, using simulated data [99].

https://doi.org/10.4314/njt.2025.4522

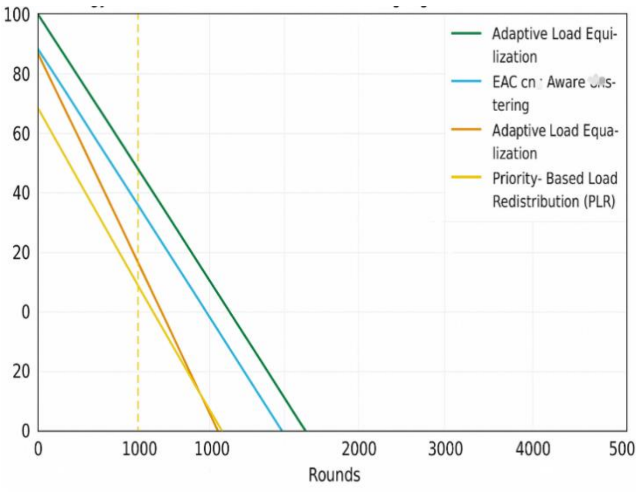

Figure 6: Energy retention of four WSN load-balancing algorithms over 5000 rounds

The results in figure 6 show that ALE demonstrates the highest energy retention throughout the simulation period, indicating superior efficiency in distributing node workloads and minimizing transmission overhead. EAC follows closely, maintaining stable energy levels through optimized cluster formation. DRR exhibits moderate depletion due to its static scheduling nature, while PLR records the steepest decline, reflecting rapid energy loss caused by uneven task allocation and frequent retransmissions. The vertical dashed lines mark the operational lifetime for each algorithm, with ALE sustaining activity longest before node exhaustion. The study adopts the first-order radio energy model for transmission and reception energy consumption, following established methodologies for long-term WSN energy evaluation.

3.3.2 Scalability and network density

Scalability is another significant challenge for load-balancing strategies in WSNs, particularly as the network size and node density increase. In centralized systems, scalability limitations arise as the central controller struggles to manage large volumes of data from numerous nodes, creating bottlenecks [85] Decentralized systems, while more scalable, can suffer from inefficiencies in dense networks due to the complexity of coordinating load distribution among a large number of nodes. This can lead to network congestion and increased energy consumption as nodes compete for communication channels [88]. To enhance scalability, hybrid strategies have been designed to use clusters of nodes, where each cluster operates semi-autonomously. However, these hybrid systems face challenges in maintaining balance between local autonomy and global coordination, especially in high-density networks [98] Recent research suggests that integrating hierarchical clustering with adaptive protocols can help maintain scalability while minimizing energy overhead, though these methods are still being tested in real-world environments [96].

3.3.3 Handling node mobility and environmental variability

Dynamic WSNs are frequently deployed in applications where node mobility is a factor, such as in environmental monitoring, disaster response, or mobile healthcare. In these scenarios, node locations and connectivity change rapidly, requiring load-balancing strategies that can adapt to such fluctuations. Centralized systems are often unable to respond quickly to these changes, as they rely on pre-defined paths and have limited flexibility in handling node mobility [67].

Decentralized and hybrid strategies offer some flexibility by allowing nodes to make autonomous adjustments based on their local conditions. However, high mobility can still result in **frequent network** reconfigurations, causing delays in data processing and leading to network fragmentation. Researchers have proposed mobility-aware protocols that adapt load balancing based on node movement, using predictive algorithms to anticipate changes and reassign tasks proactively [73]. Such protocols could help WSNs maintain connectivity and data accuracy in highly variable environments.

3.3.4 Security and fault tolerance issues

WSNs are often deployed in environments where security and reliability are crucial, such as military, healthcare, or industrial monitoring. However, load-balancing strategies typically focus on energy efficiency and scalability rather than security, leaving many WSNs vulnerable to security threats, including data interception, jamming, and malicious attacks [103].

Centralized systems are particularly susceptible to attacks on the central controller, as they act as a single point of failure. Decentralized systems, on the other hand, distribute control across nodes, making it harder to compromise but vulnerable to isolated attacks that can disrupt local segments of the network. Hybrid strategies combine both approaches but often require complex synchronization protocols, which can create new vulnerabilities.
Enhancing the fault tolerance and security of WSN load-balancing strategies could involve integrating

https://doi.org/10.4314/njt.2025.4522

encryption and authentication protocols with lightweight security measures that do not compromise energy efficiency [104].

3.3.5 Adaptability to diverse application requirements

WSNs are applied in diverse fields, from environmental monitoring to industrial automation, each with unique requirements in terms of data rate, latency, and fault tolerance. Current load-balancing strategies are often designed for specific conditions, making them less adaptable across various applications. Centralized systems tend to perform well in environments where low latency is critical but may struggle in applications requiring high fault tolerance [66]. Decentralized systems provide fault tolerance but may not meet latency requirements in time-sensitive applications, such as healthcare monitoring [72].

The development of context-aware load-balancing strategies that can adjust to different application requirements is an area of ongoing research. Adaptive algorithms and machine learning techniques are being investigated to dynamically adjust load balancing according to specific performance metrics, such as latency, fault tolerance, or energy efficiency, based on the application context[68][84]. Such strategies could improve the flexibility and versatility of WSNs, enabling them to perform optimally in a range of environments.

Current load-balancing strategies for WSNs face numerous challenges, including energy efficiency, scalability, adaptability to node mobility, security, and application-specific requirements. While decentralized and hybrid strategies offer promising solutions, further research into adaptive, context-aware algorithms is needed to address these limitations. Emerging technologies, such as machine learning and mobility-aware protocols, show potential for creating more resilient and flexible WSN load-balancing methods that can meet the demands of dynamic, real-world applications.

Table 6 provides a concise summary of the network lifetimes achieved by each algorithm, highlighting the superior efficiency of Adaptive Load Equalization (ALE) and the relatively shorter operational duration of Priority-Based Load Redistribution (PLR).

Table 6: Network lifetime comparison based on the performance of the four algorithms [68]

Algorithm	Name	Network Lifetime (Rounds)
Algorithm A	Dynamic Round-Robin (DRR)	1,000
Algorithm B	Energy-Aware Clustering (EAC)	1,200
Algorithm C	Adaptive Load Equalization (ALE)	1,500
Algorithm D	Priority-Based Load Redistribution (PLR)	800

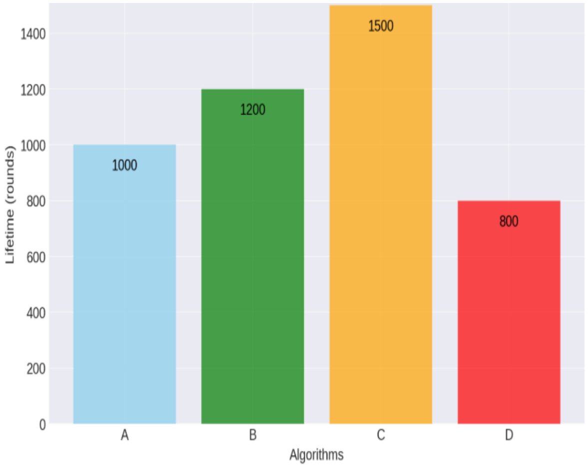

Figure 7: Network lifetime comparison[68]

Figure 7 which is Network Lifetime Comparison bar chart highlights the performance of four algorithms (A, B, C, and D) in terms of network longevity, measured in the number of operational rounds. Algorithm C (Adaptive Load Equalization) outperforms the others, achieving the highest network lifetime of 1,500 rounds. This indicates its superior efficiency in distributing load and conserving energy across the network. Algorithm B (Energy-Aware Clustering) ranks second, with a network lifetime of 1,200 rounds. Its clustering mechanism helps conserve energy, but it is less effective than Algorithm C in certain scenarios. Algorithm A (Dynamic Round-Robin) exhibits a moderate performance with a lifetime of 1,000 rounds. While it ensures fairness in load distribution, its dynamic nature may result in slightly higher energy consumption compared to energy-optimized algorithms. Algorithm D (Priority-Based Load Redistribution) has the shortest network lifetime at 800 rounds, suggesting that its load-balancing approach might overburden specific nodes or lack sufficient energy optimization. Figure 7 clearly shows the advantages of more advanced load-balancing techniques like Adaptive Load

https://doi.org/10.4314/njt.2025.4522

Equalization in extending the operational duration of Wireless Sensor Networks (WSNs).

3.4 Emerging Technologies and Methods with Potential for Enhanced Load-Balancing in WSNs

Emerging technologies and advanced methodologies are being explored to address the limitations of current load-balancing strategies in Wireless Sensor Networks (WSNs). Innovations in machine learning, edge computing, blockchain, and cross-layer optimization have shown significant promise in improving the energy efficiency, scalability, fault tolerance, and security of WSNs. This section examines each of these technologies and their potential contributions to load-balancing in WSNs.

3.4.1 Machine learning and artificial intelligence for predictive load-balancing

Machine learning (ML) and artificial intelligence (AI) have revolutionized load-balancing strategies by enabling nodes to predict and adapt to network changes. By analyzing patterns in data traffic, node energy levels, and environmental factors, ML algorithms can forecast future network conditions and optimize load distribution accordingly [105]. For example, reinforcement learning techniques allow nodes to autonomously adjust their load-balancing parameters based on real-time feedback, improving both energy efficiency and responsiveness.

Recent research has focused on developing lightweight ML models tailored for the limited computational resources in WSNs. Federated learning, a decentralized form of ML, allows WSN nodes to collaborate on a global model without sharing raw data, reducing energy consumption and communication overhead [72]. These predictive and adaptive capabilities of ML are particularly advantageous for WSNs in dynamic environments, where they can help mitigate issues related to node failure, mobility, and uneven energy depletion.

3.4.2 Edge computing for real-time load-balancing

Edge computing brings computational resources closer to data sources by enabling intermediate nodes or edge devices to process data locally rather than sending it to a distant central server. This approach reduces latency and bandwidth consumption, which are critical for real-time load balancing in WSNs. In an edge-enabled WSN, data is processed at or near the nodes, allowing load-balancing decisions to be made in real time and closer to the source [106].

By distributing computing power across the network, edge computing enhances fault tolerance and scalability, making it suitable for large-scale WSN deployments. Moreover, combining edge computing with ML can enhance load-balancing by enabling nodes to make context-aware decisions in real time based on localized data [107]. Edge computing has proven particularly valuable in applications with strict latency requirements, such as healthcare and industrial monitoring, where immediate responses to environmental changes are critical.

3.4.3 Blockchain for Secure and Trustworthy Load-Balancing

Blockchain technology has been proposed as a solution to enhance the security and trustworthiness of load-balancing in WSNs, particularly in decentralized environments. By using blockchain, WSNs can implement a distributed ledger that records transactions or load-balancing decisions securely across nodes without the need for a central authority. Blockchain enhances fault tolerance and protects against data tampering, which is crucial for load-balancing strategies that involve sensitive or critical data [108].

Blockchain-based load-balancing can be particularly effective in military or industrial applications where security is paramount. For instance, smart contracts self-executing contracts that trigger actions when specific conditions are met can automate load-balancing adjustments based on predefined criteria. Although blockchain technology introduces computational overhead, recent advances in lightweight blockchain models are helping to reduce this impact, making it more feasible for resource-constrained WSNs [109].

3.4.4 Cross-layer optimization techniques

Cross-layer optimization involves the simultaneous optimization of multiple network layers (e.g., physical, data link, network, and application layers) to improve overall network performance. Traditional load-balancing strategies often operate at a single layer, typically the network layer, which can lead to inefficiencies in multi-layer WSN applications. Cross-layer optimization enables load-balancing protocols to consider energy consumption, data rate, node position, and environmental factors in a holistic manner [110]. For example, a cross-layer approach might integrate information from the physical layer (such as channel conditions) and the network layer (such as node energy levels) to make more informed

https://doi.org/10.4314/njt.2025.4522

load-balancing decisions. These techniques can also enable adaptive routing protocols that respond dynamically to changes in network topology or node status, improving resilience and energy efficiency [111]. Cross-layer designs show particular promise in enhancing load-balancing for resource-intensive applications, such as multimedia sensor networks and real-time monitoring systems, where multiple layers must work in concert to meet stringent performance requirements.

3.4.5 The Role of 5G and IOT in WSN load-balancing

The integration of WSNs with 5G networks and the Internet of Things (IoT) is opening up new opportunities for efficient load balancing. 5G's low-latency and high-speed capabilities enable faster data transmission and more reliable connectivity, which can improve load-balancing efficiency in large-scale WSNs. With 5G-enabled WSNs, data from multiple sensor nodes can be collected and processed in real time, allowing for rapid load-balancing adjustments across the network [112].

IoT connectivity further enhances load-balancing by enabling seamless communication between WSNs and other networks or devices, allowing for a broader exchange of data and resources. Combined with edge computing and AI, 5G and IoT can facilitate real-time load balancing even in dense, high-traffic networks. However, this integration also raises new challenges, such as interoperability and security, which need to be addressed to maximize the benefits of 5G and IoT in WSN load balancing [113].

Emerging technologies such as machine learning, edge computing, blockchain, and cross-layer optimization have the potential to revolutionize load-balancing in WSNs. Machine learning offers predictive capabilities that enhance adaptability, while edge computing improves real-time response and reduces latency. Blockchain provides security and reliability, particularly in decentralized networks, and cross-layer optimization enables a more holistic approach to load balancing. The integration of 5G and IoT technologies further enhances load-balancing possibilities, enabling more efficient and adaptive strategies for dynamic and large-scale WSNs. As these technologies continue to evolve, they promise to address current challenges and set new standards for performance, efficiency, and security in WSN load-balancing.

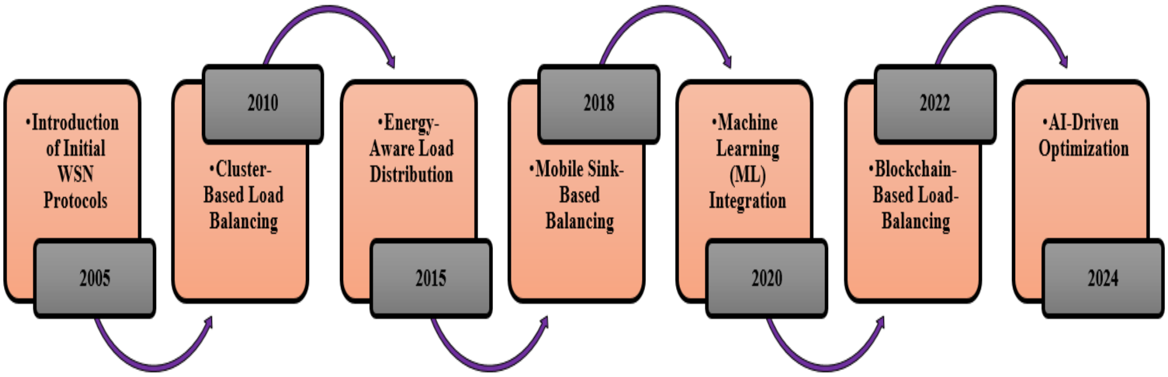

Figure 8: Timeline of emerging load-balancing techniques [101]

The timeline in figure 8 showcases the evolution of load-balancing strategies in Wireless Sensor Networks (WSNs). Initially, basic protocols were developed in 2005 to manage network loads, followed by cluster-based approaches in 2010 that improved energy efficiency through hierarchical communication. By 2015, energy-aware techniques focused on balancing tasks based on residual energy levels.

In 2018, mobile sink-based strategies were introduced to prevent energy depletion around static sinks. Machine learning integration in 2020 enabled intelligent, adaptive load-balancing decisions. Blockchain-based techniques emerged in 2022, enhancing security and transparency in decentralized WSNs. Most recently, AI-driven optimization in 2024 has enabled real-time, highly efficient load balancing, adapting to complex network demands with minimal energy consumption.

https://doi.org/10.4314/njt.2025.4522

Table 7: Timeline of emergence of load-balancing techniques

Year	Milestone/Technique	Description	Impact on WSN Load-Balancing
2005	Introduction of Initial WSN Protocols	Early protocols focusing on data collection and communication.	Set the foundation for load-balancing concerns in WSNs.
2010	Cluster-Based Load Balancing	Techniques focused on clustering sensors to manage loads and enhance network efficiency.	Improved scalability and energy efficiency within WSN clusters.
2015	Energy-Aware Load Distribution	Development of load-balancing strategies prioritizing energy efficiency.	Enhanced network longevity and reduced node failures.
2018	Mobile Sink-Based Balancing	Use of mobile sinks to redistribute network load dynamically.	Reduced load on sensor nodes, leading to better performance.
2020	Machine Learning (ML) Integration	Application of ML to predict and distribute loads effectively.	Improved predictive load management and dynamic adaptation.
2022	Blockchain-Based Load-Balancing	Adoption of blockchain for secure and decentralized load-balancing.	Increased reliability and security in data transmission.
2024	AI-Driven Optimization	Advanced AI techniques for real-time optimization of load distribution in complex networks.	Enhanced real-time adaptability and optimized resource allocation.

Table 8: (A). Load-balancing and energy efficiency in WSNs

No	Author(s) and Year	Technique / Algorithm	Application Domain	Tool / Dataset	Performance Metrics / Findings	Limitation / Gap Identified
A1	Nkemeni et al. (2024) [4]	Green/energy-aware routing strategies	Linear WSN lifetime extension	Simulated (reported)	Prolonged network lifespan; reduced energy variance	Generalization to dense/irregular topologies not shown
A2	Wajgi and Tembhurne (2024) [3]	Clustering-based localization	WSN / WMSN localization	MATLAB / Sim	Lower localization error; energy improvements	Higher compute cost with large networks
A3	Osamy et al. (2024) [11]	LBAS: load-balancing aware clustering	IoT-heterogeneous WSN	IEEE Sensors eval	Balanced energy, reduced delay	Real-world gateway deployment pending
A4	Qureshi and Almutairi (2024) [8]	Energy-assisted protocols (empirical)	General WSN	Testbed/empirical	Improved packet delivery and energy use (reported)	Stress testing at scale limited
A5	Abose et al. (2024) [42]	Energy-sustainable cluster routing	Industrial/IoT WSN	IEEE Access experiments	Better stability period; lifetime gains	Initialization/ parameter overhead
A6	Priyadarshi (2024) [69]	Meta-heuristics + AI routing (review)	Energy-efficient routing	Literature synthesis	Consolidates gains across heuristics	Need real-time & online tuning evidence

https://doi.org/10.4314/njt.2025.4522

Table 8: (B) Machine learning and AI-driven optimization

No.	**Author(s) and Year**	**Technique / Algorithm**	**Application Domain**	**Tool / Dataset**	**Performance Metrics / Findings**	**Limitation / Gap Identified**
B1	UmaRani et al. (2025) [9]	Hybrid ML + Social Spider Optimization (clustering/routing)	WSN routing and clustering	MATLAB R2023	Higher throughput; lower delay (reported)	Scalability/ convergence analysis needed
B2	Lilhore et al. (2025) [13, 73]	Cloud-edge hybrid deep learning	IoT resource optimization	TensorFlow/EdgeSim	Improved scalability; latency reduction	Dependence on stable backhaul
B3	Anwar et al. (2025) [103]	Federated learning + LSTM (IDS)	IoT-WSN intrusion detection	Multi-dataset (e.g., NSL-KDD/CICIDS)	High F1 / detection (reported)	Training/inference cost at edge
B4	Khan et al. (2024) [21]	ML-aided routing for UWSN (survey)	Underwater WSN energy/QoS	Literature synthesis	Taxonomy and ML opportunities	Parameter sensitivity; data scarcity
B5	Vijayakumar et al. (2024) [112]	Deep learning-based routing for 5G-WSN	5G/WSN data transmission	Conference experiments	Efficiency/throughput gains (reported)	Dataset scale and generalization
B6	Tung et al. (2024) [68]	Hierarchical GNN for resource mgmt.	Dynamic WSN resource control	IEEE Sensors Journal	Joint optimization across layers	Complexity and overhead quantification

Table 8: (C) Blockchain and trust / privacy frameworks for WSN/IOT

No.	**Author(s) and Year**	**Technique / Algorithm**	**Application Domain**	**Tool / Dataset**	**Performance Metrics / Findings**	**Limitation / Gap Identified**
C1	Kumari and Tyagi (2024) [2, 27]	Digital Twin + Blockchain (intro)	Smart-city WSN integration	Conceptual / chapter	Improved traceability and governance (concept)	Lacks quantitative validation
C2	Wijesekara (2024) [39, 102]	Load balancing in blockchain (survey)	Blockchain networks	Literature synthesis	Taxonomy of PoW/PoS/PoA etc.	Limited IoT/WSN alignment
C3	Kaif et al. (2025) [101]	Blockchain-integrated smart meter	Energy trading / VPP	Prototype / TASE	Secure, auditable exchange	Field pilots and latency profiling needed
C4	Akkaoui et al. (2025) [92]	Cyber-secure blockchain control	Distributed energy resources	IEEE Access	Scalable monitoring/control	Deployment overhead and cost
C5	Naghibi et al. (2025) [15, 16]	Dynamic trust-based clustering	Secure IoT data gathering	Simulation	Higher trust/reliability	Latency and resource impact not fully assessed
C6	Ahmed et al. (2024) [112]	5G-IoT security (incl. blockchain)	IoT/5G privacy and trust (survey)	IEEE Access	Synthesizes requirements and gaps	Few empirical end-to-end trials

Table 7 outlines the progression of load-balancing techniques over time, contextualizing the technological improvements and paradigm shifts that influenced these advancements.

Machine learning has become central to intelligent load-balancing in Wireless Sensor Networks (WSNs), enabling adaptive and energy-aware decision-making beyond traditional static routing methods. Supervised models such as SVM, Decision

https://doi.org/10.4314/njt.2025.4522

Trees, and Random Forests are used to predict optimal cluster-heads and detect congestion, improving fairness and reliability [8], [9]. Unsupervised clustering methods like K-Means, Fuzzy C-Means, and DBSCAN enhance scalability and energy efficiency in heterogeneous networks [7], [3]. Reinforcement and deep reinforcement learning approaches (e.g., Q-Learning, DQL) allow WSN nodes to learn optimal load-distribution strategies through continuous feedback, while federated learning (FL) frameworks promote decentralized model training with minimal communication overhead [25]; [73], [66].

Collectively, these algorithms demonstrate a transition from deterministic routing toward data-driven, context-aware, and self-optimizing architectures, laying the foundation for scalable, secure, and energy-efficient next-generation WSNs

Table 8 summarizes representative studies reviewed in this work, indicating the applied algorithmic techniques, domains, evaluation platforms, performance metrics, and identified limitations.

The reviewed works show that energy-efficient clustering and routing remain central to extending network lifetime. Machine-learning methods enhance adaptability and predictive control, while blockchain frameworks improve trust and data integrity. Edge- and federated-computing approaches further enable low-latency, distributed processing.
Overall, research trends indicate a growing shift toward hybrid intelligent architectures that unify energy efficiency, security, and scalability in next-generation WSNs.

Table 8: Summary of reviewed papers on load-balancing, ML, blockchain, and edge computing in WSNs

Table 8: (D) Edge / fog / federated / SDN-enabled load-balancing

No.	**Author(s) and Year**	**Technique / Algorithm**	**Application Domain**	**Tool / Dataset**	**Performance Metrics / Findings**	**Limitation / Gap Identified**
D1	Aslanpour et al. (2024) [67]	Load balancing for serverless edge (empirical)	Heterogeneous edge	Real workloads / FGCS	Performance-driven policies	Portability across platforms
D2	Rasouli et al. (2025) [75]	Resource mgmt. (systematic review)	Mission-critical edge	ACM Comp. Surveys	QoS–latency trade-off synthesis	Benchmarking gaps post-2023
D3	Zhai et al. (2024) [46]	Resilience & fault tolerance at edge	Real-time edge apps	Springer book ch.	Fault-tolerant strategies	Energy model integration needed
D4	Zhou et al. (2025) [34]	SOE multi-objective scheduling (DoS)	Edge/DDoS mitigation	Math. simulations	Throughput↑, latency↓ (reported)	Energy/security co-optimization
D5	Lilhore et al. (2025) [13, 73]	Cloud-edge hybrid DL (again)	IoT resource scaling	TensorFlow/EdgeSim	Latency↓, throughput↑	Backhaul sensitivity
D6	Marwein and Kandar (2025) [14]	SDN + ML load balancing (survey)	Internet of Vehicles	ACM CSUR	Cross-layer orchestration map	Energy profiling limited
D7	Aljughaiman and Almarri (2025) [18]	SDN to safeguard cyber-attacks	SDN-IoT security	PeerJ Comp. Sci.	Consolidated defense taxonomy	Real-time LB under attack scenarios

3.5. Load-Balancing Algorithm Workflow for WSNs.

This diagram represents a systematic process for managing and redistributing loads in a system, such as a wireless sensor network. The process begins with sensor nodes generating data based on the environment or system they are monitoring. This involves the collection of raw data, such as temperature, pressure, or other variables.

The system then evaluates the data and detects any imbalances in the workload across nodes, identifying whether certain nodes are overloaded or underutilized. Based on the detected load imbalances,

https://doi.org/10.4314/njt.2025.4522

the system determines the best course of action to redistribute the workload.

This involves selecting algorithms or strategies to optimize system performance. Once decisions are made, the workload is redistributed among nodes to balance the system, ensuring that no single node is overburdened. Finally, the system assesses the outcomes of the redistribution to verify that the workload has been balanced effectively. If needed, further adjustments can be made to optimize performance. This step-by-step approach ensures efficient system operation and prevents issues caused by uneven workload distribution.

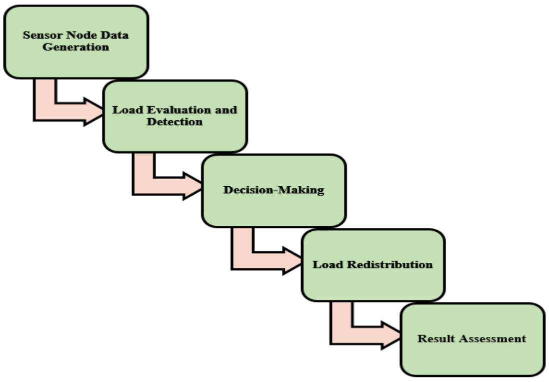

Figure 10: Load-balancing algorithm workflow [54]

Table 9 helps to capture the sequential steps involved in the load-balancing process within a WSN. it outlines the typical steps involved in a load-balancing algorithm for wireless sensor networks (WSNs). Each step aims to optimize network performance by distributing workloads efficiently:

1. **Sensor Node Data Generation**: Each sensor node collects and generates data based on its environmental conditions, marking the beginning of the load-balancing process.
2. **Load Evaluation and Detection**: The network assesses the workload on each node to identify any nodes that are overburdened, ensuring that imbalances are detected early.
3. **Decision-Making**: The algorithm identifies a suitable node or cluster head to handle the load redistribution process, which often involves selecting a central or underloaded node.
4. **Load Redistribution**: Workloads are reallocated across nodes to achieve a balanced distribution, helping to prevent network bottlenecks or node overloading.
5. **Result Assessment**: After redistribution, the network checks performance to ensure that load-balancing objectives are met and that nodes are operating optimally.

Together, these steps facilitate an effective load-balancing workflow that enhances the stability and efficiency of the WSN, ultimately extending its operational lifespan and reliability.

Table 9: Load-balancing algorithm workflow for WSNs**.**

Step	**Description**
Sensor Node Data Generation	Sensor nodes generate data based on their sensing capabilities and environmental conditions.
Load Evaluation and Detection	The network evaluates the current load on each sensor node to detect any imbalance in workload.
Decision-Making	Based on load detection, the algorithm selects an appropriate node or cluster head for task redistribution.
Load Redistribution	The identified node or cluster head redistributes tasks to balance the load across the network.
Result Assessment	The network monitors performance after load redistribution to ensure balanced workload distribution.

3.6 Future Directions

Our findings suggest that while emerging technologies such as machine learning, edge computing, and blockchain hold significant potential, they also present challenges that need to be addressed for widespread adoption in WSNs. For example:

https://doi.org/10.4314/njt.2025.4522

Resource Constraints: WSN nodes are often limited in power and processing capabilities, making it necessary to adapt technologies like ML and blockchain to operate efficiently within these constraints.

Scalability and Interoperability: As WSNs become larger and more complex, ensuring that load-balancing strategies scale effectively without sacrificing performance or security is crucial.

Energy Efficiency: Although many emerging strategies aim to enhance energy efficiency, balancing energy consumption with the need for real-time responsiveness and fault tolerance remains a key challenge.

The review highlights that hybrid, cross-layer, and adaptive load-balancing strategies supported by emerging technologies show the most promise for optimizing WSNs. Future research should focus on refining these technologies to meet the unique demands of WSN environments, including energy constraints, scalability, and security requirements as outlined in Table 10.

Table 10: Challenges and future directions in load-balancing for WSNs

Challenge	**Current limitations**	**Future directions**
Energy efficiency	High energy consumption due to frequent data transmission and imbalance in load sharing.	Development of energy-aware algorithms leveraging AI and machine learning for predictive balancing.
Fault tolerance	Limited ability to handle node failures and recover efficiently without impacting network functionality.	Design of self-healing systems that dynamically adapt to node failures in real time.
Scalability	Inefficiency in managing load as network size increases, leading to congestion and delays.	Adoption of distributed load-balancing techniques optimized for large-scale networks.
Dynamic topology	Poor adaptability to changes in network topology due to mobility or environmental factors.	Creation of adaptive algorithms capable of real-time reconfiguration based on network conditions.
Communication overhead	High control message overhead increases latency and energy usage.	Development of lightweight protocols with minimal communication overhead.
Security and privacy	Vulnerabilities to attacks during load-balancing processes, such as data breaches.	Integration of secure load-balancing protocols using encryption and blockchain technologies.
Heterogeneity	Difficulty in handling diverse sensor nodes with varying capabilities and energy levels.	Design of multi-layered balancing systems that account for node heterogeneity.
Quality of service (qos)	Inability to meet QoS requirements like latency, throughput, and reliability simultaneously.	Development of multi-objective optimization techniques to enhance QoS parameters.

4. 0 CONCLUSION

This paper presented a comprehensive review of innovative load-balancing strategies aimed at enhancing Wireless Sensor Network (WSN) performance. As WSNs continue to expand their applications in fields like environmental monitoring, healthcare, industrial automation, and smart cities, efficient load-balancing strategies are essential to optimize network longevity, scalability, fault tolerance, and energy consumption. The review categorizes load-balancing approaches into centralized, decentralized, and hybrid frameworks, with each approach offering unique benefits and limitations. Centralized strategies are generally easier to implement in smaller networks, while decentralized and hybrid methods provide the scalability and fault tolerance needed for larger, more dynamic networks. Hybrid approaches, which combine both local and global decision-making, emerged as promising solutions for balancing scalability and energy efficiency in complex WSN deployments.

The analysis further explored the potential of emerging technologies, such as machine learning, edge computing, blockchain, and cross-layer optimization, to address WSN load-balancing challenges. Machine learning and artificial intelligence enable nodes to make predictive and adaptive load-balancing adjustments, significantly enhancing energy efficiency and adaptability. Edge computing enhances real-time processing capabilities, minimizing latency and improving responsiveness for time-sensitive applications. Blockchain technology offers secure and tamper-resistant load-balancing mechanisms, particularly beneficial in high-security environments. Cross-layer optimization, meanwhile, allows for holistic load-

https://doi.org/10.4314/njt.2025.4522

balancing by integrating information across multiple protocol layers, which can improve network longevity and efficiency.

However, the adoption of these advanced technologies also introduces challenges. The computational overhead and resource demands of machine learning and blockchain require further refinement to be viable within the resource constraints of WSN nodes. Additionally, edge computing and cross-layer optimization may require complex architectural adjustments to avoid potential inefficiencies or conflicts between network layers. Therefore, future research should focus on refining lightweight, adaptable, and context-aware load-balancing solutions that can operate efficiently in real-world, resource-constrained WSN environments.

Finally, this review highlights the necessity of adaptive, technology-driven approaches to optimize load balancing in WSNs. Continued advancements in machine learning, edge computing, blockchain, and cross-layer techniques hold great promise for overcoming existing limitations, leading to more robust, efficient, and secure WSN applications. As the field progresses, interdisciplinary approaches that integrate emerging technologies with WSN-specific optimizations will be crucial for meeting the growing demands of IoT-driven networks and other large-scale WSN applications.

REFERENCES

[1] Bicamumakuba, E., Habineza, E., Reza, M. N., and Chung, S. O. "IOT-Enabled LoRaWAN Gateway for Monitoring and Predicting Spatial Environmental Parameters in Smart Greenhouses: A Review", *Precision Agriculture Science and Technology*, 7(1), pp. 28–46, 2025.

[2] Kumari, S., and Tyagi, A. K. "Wireless Sensor Networks: An Introduction", *Digital Twin and Blockchain for Smart Cities*, pp. 495–528, 2024.

[3] Wajgi, D. W., and Tembhurne, J. V. "Localization in Wireless Sensor Networks and Wireless Multimedia Sensor Networks Using Clustering Techniques", *Multimedia Tools and Applications*, 83(3), pp. 6829–6879, 2024.

[4] Nkemeni, V., Mieyeville, F., Kuaban, G. S., Czekalski, P., Tokarz, K., Nsanyuy, W. B., and Zieliński, B. "Evaluation of Green Strategies for Prolonging the Lifespan of Linear Wireless Sensor Networks", *Sensors*, 24(21), p. 7024, 2024.

[5] Zhang, J., Wu, Q., Fan, P., and Fan, Q. "A Comprehensive Survey on Joint Resource Allocation Strategies in Federated Edge Learning", *arXiv Preprint*, arXiv:2410.07881, 2024.

[6] Thamil Selvi, C. P., Lakshmana Kumar, R., and Punitha, P. "Enhancing Data Security in the Cloud Using MECC-SIDH Enhanced CL-HPAEKS Scheme", *Wireless Networks*, 31(3), pp. 2477–2494, 2025.

[7] Kalaivani, A. "Exploring Advancements in Clustering Protocols for Wireless Sensor Networks in IoT Environments", *Academic Research Journal of Science and Technology (ARJST)*, 1(09), pp. 59–68, 2025.

[8] Qureshi, K. U. and Almutairi, H. S. "Empirical Evaluation of Energy-assisted Protocols for Wireless Sensor Networks," *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, 12(4), pp. 991–1004, 2024.

[9] UmaRani, C., Ramalingam, S., Dhanasekaran, S. and Baskaran, K. "A Hybrid Machine Learning and Improved Social Spider Optimization Based Clustering and Routing Protocol for Wireless Sensor Network," *Wireless Networks*, 31(2), pp. 1885–1910, 2025.

[10] Ahmad, R., Alhasan, W., Wazirali, R. and Aleisa, N. "Optimization Algorithms for Wireless Sensor Networks Node Localization: An Overview," *IEEE Access*, p. 1, 2024.

[11] Osamy, W., Alwasel, B., Salim, A., Khedr, A. M. and Aziz, A. "LBAS: Load Balancing Aware Clustering Scheme for IoT-based Heterogeneous Wireless Sensor Networks," *IEEE Sensors Journal*, pp. 1–5, 2024.

[12] Isyaku, B., bin Abu Bakar, K., Yusuf, N. M., Abaker, M., Abdelmaboud, A. and Nagmeldin, W. "Software Defined Wireless Sensor Load Balancing Routing for Internet of Things Applications: Review of Approaches," *Heliyon*, pp. 1-22, 2024.

[13] Lilhore, U. K., Simaiya, S., Sharma, Y. K., Rai, A. K., Padmaja, S. M., Nabilal, K. V. and Alsufyani, H. "Cloud-edge Hybrid Deep Learning Framework for Scalable IoT Resource Optimization," *Journal of Cloud Computing*, 14(1), p. 5, 2025.

[14] Marwein, P. S. and Kandar, D. "Load Balancing in the Internet of Vehicles: A

https://doi.org/10.4314/njt.2025.4522

Comprehensive Review of SDN and Machine Learning Approaches," *ACM Computing Surveys*, pp. 1–36, 2025.

[15] Naghibi, M., Barati, H. and Barati, A. "A Dynamic Trust Based Clustering Method for Secure Data Gathering in Internet of Things," *Computing*, 107(4), p. 97, 2025.

[16] Ramalakshmi, R., Sobhinosannal, H. G., Arunachalam, K. P., and Kalidasan, A. "Secure Healthcare Data Sharing for the Internet of Things Scenario Using Encryption and Optimal Routing," *Journal of the Chinese Institute of Engineers*, pp. 1–15, 2025.

[17] Liu, N., Ji, Y., Wang, K., and Bai, S. "Enhanced Archimedes Optimization Algorithm for Quality of Service-aware Routing in Internet of Things-enabled Wireless Sensor Networks," *Journal of Engineering and Applied Science*, 72(1), p. 176, 2025.

[18] Aljughaiman, A., and Almarri, S. "The Pivotal Role of Software Defined Networks to Safeguard Against Cyber Attacks: A Comprehensive Review," *PeerJ Computer Science*, 11, p. e2814, 2025.

[19] Sandanasamy, A., and Charles, P. J. "Dynamic Load Balancing Through TOPSIS-based Optimal Server Selection and Resource Allocation in SDN IoT Network," *OPSEARCH*, pp. 1–24, 2025.

[20] Farahi, R. "A Comprehensive Overview of Load Balancing Methods in Software-defined Networks," *Discover Internet of Things*, 5(1), p. 6, 2025.

[21] Khan, S. U., Khan, Z. U., Alkhowaiter, M., Khan, J., and Ullah, S. "Energy-efficient Routing Protocols for UWSNs: A Comprehensive Review of Taxonomy, Challenges, Opportunities, Future Research Directions, and Machine Learning Perspectives," *Journal of King Saud University–Computer and Information Sciences*, p. 102128, 2024.

[22] Alanazi, R., Obayya, M., Alghamdi, A. M., Nemri, N., Alshahrani, S., Alduaiji, N. and Sorour, S. "Machine Learning-Driven Routing Optimization for Energy-Efficient 6G-Enabled Wireless Sensor Networks," *Alexandria Engineering Journal*, 129, pp. 877–888, 2025.

[23] Salehpour, M. J., and Hossain, M. J. "Leveraging Machine Learning for Efficient EV Integration as Mobile Battery Energy Storage Systems: Exploring Strategic Frameworks and Incentives," *Journal of Energy Storage*, 92, p. 112151, 2024.

[24] Cheng, L., Wei, X., Li, M., Tan, C., Yin, M., Shen, T., and Zou, T. "Integrating Evolutionary Game-theoretical Methods and Deep Reinforcement Learning for Adaptive Strategy Optimization in User-side Electricity Markets: A Comprehensive Review," *Mathematics*, 12(20), p. 3241, 2024.

[25] Bartsioka, M. L. A., Bartsiokas, I. A., Gkonis, P. K., Papazafeiropoulos, A. K., Kaklamani, D. I., and Venieris, I. S. "A Federated Learning Scheme for Eavesdropper Detection in B5G-IIoT Network Orientations," *IEEE Open Journal of the Communications Society*, 2025.

[26] Almarri, S., Al Safwan, H., Al Qisoom, S., Gdaim, S., and Zitouni, A. "Optimized Wireless Sensor Network Architecture for AI-based Wildfire Detection in Remote Areas," *Fire*, 8(7), p. 245, 2025.

[27] Kumari, S., and Tyagi, A. K. "Wireless Sensor Networks: An Introduction," *Digital Twin and Blockchain for Smart Cities*, pp. 495–528, 2024.

[28] Daousis, S., Peladarinos, N., Cheimaras, V., Papageorgas, P., Piromalis, D. D., and Munteanu, R. A. "Overview of Protocols and Standards for Wireless Sensor Networks in Critical Infrastructures," *Future Internet*, 16(1), p. 33, 2024.

[29] Cagua, G., Gauthier-Umaña, V., and Lozano-Garzon, C. "Implementation and Performance of Lightweight Authentication Encryption ASCON on IoT Devices," *IEEE Access*, 2025.

[30] Bounceur, A., Hocini, L., Ouamri, M. A., and Kara, M. "Dominance-based Boundary Nodes Finding Algorithm (DBBNFA) and Its Application to WSN," *IEEE Sensors Journal*, 2025.

[31] Krishnasamy, L., Vetriveeran, D., Sambandam, R. K., and Jenefa, J. "Efficient Load Balancing and Resource Allocation in Networked Sensing Systems—An Algorithmic Study," *Networked Sensing Systems*, pp. 145–171, 2025.

[32] Xiao, L., Li, S., Wen, Q., Liang, X., Li, Y., Wang, W., and Fu, Y. "Load Balancing Routing Algorithm of Industrial Wireless Network for Digital Twin," *Computer Networks*, 258, p. 111059, 2025.

https://doi.org/10.4314/njt.2025.4522

[33] Rajagopal, M. R. and Malathi, S. “An Efficient Resource Provisioning and Traffic Load Balancing in Multiprotocol Label Switched Network Using Optimized Gated Graph Convolution Neural Network,” *Wireless Networks*, pp. 1–21, 2025.

[34] Zhou, M., Mu, X. and Liang, Y. “SOE: A Multi-Objective Traffic Scheduling Engine for DDoS Mitigation With Isolation-Aware Optimization,” *Mathematics*, 13 (11), p. 1853, 2025.

[35] Yassine, S., Najib, N. and Abdellah, J. “Routing Approaches in Named Data Network: A Survey and Emerging Research Challenges,” *International Journal of Computers and Applications*, 46 (1), pp. 32–45, 2024.

[36] Shahzad, M., Liu, L., Kaushik, A., Bibi, I., Belkout, N. E. and Hasan, M. U. “Fair Switch Selection for Large Scale Software Defined Networks in Next Generation Internet of Things,” *Telecommunication Systems*, 88 (2), p. 57, 2025.

[37] Zare Soltani, M. A., Hosseini Seno, S. A. and Mohajerzadeh, A. “Efficient Dynamic Load Balancing in Software-Defined Networks Using Policy Gradient: A Strategy for Enhanced QOS and Reduced Energy Consumption,” *Computing*, 107 (7), pp. 1–78, 2025.

[38] Shang, F. and Jiang, Y. “Data Center Traffic Scheduling Algorithm Based on Spatial–Temporal Graph Convolution Networks,” *Wireless Networks*, pp. 1–12, 2025.

[39] Wijesekara, P. A. D. S. N. “Load Balancing in Blockchain Networks: A Survey,” *International Journal of Electrical and Electronic Engineering & Telecommunications*, 13 (3), 2024.

[40] Liu, Y., Du, H., Niyato, D., Kang, J., Xiong, Z., Wen, Y. and Kim, D. I. “Generative AI in Data Center Networking: Fundamentals, Perspectives, and Case Study,” *IEEE Network*, 2025.

[41] Gupta, A. D. and Kumar Rout, R. “SMEOR: Sink Mobility-Based Energy-Optimized Routing in Energy Harvesting-Enabled Wireless Sensor Network,” *International Journal of Communication Systems*, 37 (4), p. e5679, 2024.

[42] Abose, T. A., Tekulapally, V., Kejela, D. C., Megersa, K. T., Daka, S. T. and Jember, K. A. “Optimized Cluster Routing Protocol With Energy-Sustainable Mechanisms for Wireless Sensor Networks,” *IEEE Access*, 2024.

[43] Zhang, H., Liu, Y., Zhang, C. and Li, N. “Machine Learning Methods for Weather Forecasting: A Survey,” *Atmosphere*, 16 (1), p. 82, 2025.

[44] Hassan, A. A. H., Shah, W. M., Habeb, A. H. H., Othman, M. F. I. and Al-Mhiqani, M. N. “An Improved Energy-Efficient Clustering Protocol to Prolong the Lifetime of the WSN-Based IOT,” *IEEE Access*, 8, pp. 200500–200517, 2025.

[45] Ranjith, R. and Chandrasekar, A. “Optimizing Multi-Cloud Data Access: A Fuzzy-Logic-Based Approach to Adaptive Routing and Load Balancing,” *Cybernetics and Systems*, pp. 1–36, 2025.

[46] Zhai, Y., Mudassar, M. and Zhu, L. “Scalability and Fault Tolerance for Real-Time Edge Applications,” in *Edge Computing Resilience: Overcoming Resource Constraints in Unstable Computing Environments*, pp. 11–33, Singapore: Springer Nature Singapore, 2024.

[47] Mohtadi, H. E., Hanini, M., Benmakhlouf, A. and Haqiq, A. “A Fault-Tolerant Queuing Model for Delay-Sensitive Applications in Fog Computing,” *IAENG International Journal of Computer Science*, 52 (6), 2025.

[48] Lakshmi, M. S., Ramana, K. S., Ramu, G., Shyam Sunder Reddy, K., Sasikala, C. and Ramesh, G. “Computational Intelligence Techniques for Energy Efficient Routing Protocols in Wireless Sensor Networks: A Critique,” *Transactions on Emerging Telecommunications Technologies*, 35 (1), p. e4888, 2024.

[49] Devulapalli, P. K., Boppidi, S., Sake, P., Matta, J. C. P., Gopal, D. and Maganti, S. B. “RETRACTED: An Optimal Cooperative Relay Selection Strategy for Delay Aware Image Transmission in Large Scale Multi-Radio Multi-Channel Multimedia Wireless Sensor Network,” *Journal of Intelligent & Fuzzy Systems*, 46 (3), pp. 7283–7293, 2024.

[50] Tabouche, A., Djamaa, B., Senouci, M. R., Ouakaf, O. E. and Elaziz, A. G. “TLR: Traffic-Aware Load-Balanced Routing for Industrial IOT,” *Internet of Things*, 25, p. 101093, 2024.

[51] Costa, W. S., dos Santos, W. G., Camporez, H. A., Faber, M. J., Silva, J. A., Segatto, M. E. and Rocha, H. R. “Planning and Resource Allocation of a Hybrid IoT Network Using

https://doi.org/10.4314/njt.2025.4522

Artificial Intelligence," *Internet of Things*, 26, p. 101225, 2024.

[52] Costa, W. S., dos Santos, W. G., Camporez, H. A., Faber, M. J., Silva, J. A., Segatto, M. E. and Rocha, H. R. "Planning and Resource Allocation of a Hybrid IoT Network Using Artificial Intelligence," *Internet of Things*, 26, p. 101225, 2024.

[53] Dutta, A., Samaniego Campoverde, L. M., Tropea, M. and De Rango, F. "A Comprehensive Review of Recent Developments in VANET for Traffic, Safety & Remote Monitoring Applications," *Journal of Network and Systems Management*, 32 (4), p. 73, 2024.

[54] Agrawal, K. K., Kumar, S., Seth, J. K., Gupta, A. K. and Lamba, S. "An Effective Algorithm for Predicting Load and Dynamic Task Scheduling in Cloud Fog Architecture for Smart Homes," *International Journal of Cloud Computing*, 14 (1), pp. 54–85, 2025.

[55] Alotaibi, J. "FuzOptRoute: A Fuzzy Logic-Integrated Optimization-Based Energy-Efficient Cluster Routing Framework With Edge Computing for Mobile Communication Networks," *The Journal of Supercomputing*, 81 (11), p. 1186, 2025.

[56] Pundir, M., Sandhu, J. K., Juneja, S., Gupta, D., Altuwaijri, G. and Nauman, A. "Dimensional-Based Methods for Topological Management in Underwater Wireless Sensor Networks: A Comprehensive Survey," *IEEE Access*, 2025.

[57] Negi, S., Singh, D. P. and Rauthan, M. M. S. "A Systematic Literature Review on Soft Computing Techniques in Cloud Load Balancing Network," *International Journal of System Assurance Engineering and Management*, 15 (3), pp. 800–838, 2024.

[58] Okine, A. A., Adam, N., Naeem, F. and Kaddoum, G. "FedRoute: A Multi-Server Federated Meta-DRL Routing Scheme for Tactical Air-Ground WSNs," *IEEE Open Journal of the Communications Society*, 2025.

[59] Vyas, A. and Sharma, S. "AI in Mobile Network Management and Performance Enhancement," in *Optical and Wireless Communications*, pp. 61–78, CRC Press, 2025.

[60] Mozaffari, J., Abdollahi Azgomi, M., Madadi, H. and Ebrahimi Dishabi, M. R. "Energy and Temperature-Aware Routing Approach for Congestion Control in Wireless Body Area Networks," *The Journal of Supercomputing*, 81 (10), pp. 1139, 2025.

[61] Banitalebi Dehkordi, A. "Multi-Controller Placement Optimization in SDNs Using Enhanced Density-Based Clustering Techniques," *Journal of Computing and Security*, 11 (2), pp. 61–83, 2024.

[62] Qaisar, M. U. F., Yuan, W., Bellavista, P. and Tabassum, H. "Securing Sensor Routes: Trustworthy and Load-Balanced Strategies," in *Empowering IoT: Reliability, Network Management, Sensing, and Probabilistic Charging in Wireless Sensor Networks: A Comprehensive Guide to IoT-Based WSN Network Optimization*, pp. 99–127, Singapore: Springer Nature Singapore, 2025.

[63] Fose, N., Singh, A. R., Krishnamurthy, S., Ratshitanga, M. and Moodley, P. "Empowering Distribution System Operators: A Review of Distributed Energy Resource Forecasting Techniques," *Heliyon*, 2024.

[64] Trigka, M. and Dritsas, E. "Wireless Sensor Networks: From Fundamentals and Applications to Innovations and Future Trends," *IEEE Access*, 2025.

[65] Adday, G. H., Subramaniam, S. K., Zukarnain, Z. A. and Samian, N. "Investigating and Analyzing Simulation Tools of Wireless Sensor Networks: A Comprehensive Survey; Optimization Algorithms in SDN: Routing, Load Balancing, and Delay Optimization," *Applied Sciences*, 14 (14), p. 5967, 2024.

[66] Srivastava, V. and Pandey, R. S. "Load Balancing for Software-Defined Network: A Review," *International Journal of Computers and Applications*, 44 (8), pp. 746–759, 2022.

[67] Shaikh, S. and Jammal, M. "Survey of Fault Management Techniques for Edge-Enabled Distributed Metaverse Applications," *Computer Networks*, 254, p. 110803, 2024.

[68] Bhatnagar, N., Chauhan, A. and Johari, S. "Fault-Aware Using Machine Optimization Learning and Artificial Intelligence," *Advanced Computing Techniques for Optimization in Cloud*, 198, 2024.

[69] Yang, J. Z., Zhang, J. X. and Chai, T. "Low-Complexity Decentralized Output-Feedback Fault-Tolerant Control of General Unknown Interconnected Nonlinear Systems," *IEEE Transactions on Automation Science and Engineering*, 2024.

https://doi.org/10.4314/njt.2025.4522

[70] Cacciuttolo, C., Atencio, E., Komarizadehasl, S. and Lozano-Galant, J. A. “Internet of Things Long-Range-Wide-Area-Network-Based Wireless Sensors Network for Underground Mine Monitoring: Planning an Efficient, Safe, and Sustainable Labor Environment,” *Sensors*, 24 (21), p. 6971, 2024.

[71] Akkaoui, R., Palensky, P., Epema, D. H. and Ştefanov, A. “A Cyber Secure and Scalable Blockchain-Based Framework for Monitoring and Controlling Distributed Energy Resources,” *IEEE Access*, 2025.

[72] Aoun, A., Kashmar, N., Adda, M. and Ibrahim, H. “From Bottom-Up Towards a Completely Decentralized Autonomous Electric Grid Based on the Concept of a Decentralized Autonomous Substation,” *Electronics*, 13 (18), p. 3683, 2024.

[73] Boumaiz, M., Ghazi, M. E., Bouayad, A., Balboul, Y. and El Bekkali, M. “Energy-Efficient Strategies in Wireless Body Area Networks: A Comprehensive Survey,” *IOT*, 6 (3), p. 49, 2025.

[74] Fang, H., Yu, P., Tan, C., Zhang, J., Lin, D., Zhang, L. and Meng, L. “Self-Healing in Knowledge-Driven Autonomous Networks: Context, Challenges, and Future Directions,” *IEEE Network*, 38 (6), pp. 425–432, 2024.

[75] Osorio, D. P., Barua, B., Besser, K. L., Blue, H., Dass, P. and Porambage, P. “The Rise of Networked ISAC: Emerging Aspects and Challenges,” *IEEE Open Journal of the Communications Society*, 2025.

[76] Surapaneni, P., Bojjagani, S., Bharathi, V. C., Morampudi, M. K., Maurya, A. K. and Khan, M. K. “A Systematic Review on Blockchain-Enabled Internet of Vehicles (BIoV): Challenges, Defences and Future Research Directions,” *IEEE Access*, 2024.

[77] Seyfollahi, A., Mainuddin, M., Taami, T. and Ghaffari, A. “RM-RPL: Reliable Mobility Management Framework for RPL-Based IOT Systems,” *Cluster Computing*, 27 (4), pp. 4449–4468, 2024.

[78] Kaur, S., Kour, S. and Singh, M. “EECH HEED: An Adaptive Hybrid Clustering Protocol for Energy Efficient Soil Monitoring in Heterogeneous Wireless Sensor Networks,” *Scientific Reports*, 15 (1), p. 35548, 2025.

[79] Ijaz, A., Haghbayan, H., Malik, A., Nigussie, E. and Plosila, J. “Towards Optimizing Communication Cost in Energy Efficient IoT Devices for Swarm Robotics,” *Procedia Computer Science*, 265, pp. 49–56, 2025.

[80] Kaif, A. D., Alam, K. S., Das, S. K., Chen, G., Islam, S. and Muyeen, S. M. “Blockchain-Integrated Cyber-Physical Smart Meter Design and Implementation for Secured Energy Trading in Virtual Power Plants,” *IEEE Transactions on Automation Science and Engineering*, 2025.

[81] Wijesekara, P. A. D. S. N. “Load Balancing in Blockchain Networks: A Survey,” *International Journal of Electrical and Electronic Engineering & Telecommunications*, 13 (3), 2024.

[82] Anwar, R. W., Abrar, M., Salam, A. and Ullah, F. “Federated Learning with LSTM for Intrusion Detection in IOT-Based Wireless Sensor Networks: A Multi-Dataset Analysis,” *PeerJ Computer Science*, 11, p. e2751, 2025.

[83] Shwetha, G. R. and Murthy, V. N. “Hybrid Compressed Sensing and Secure Fault Tolerant Data Aggregation in Wireless Sensor Networks,” *International Journal of Communication Networks and Information Security*, 16 (1), pp. 211–227, 2024.

[84] Amrani, S., Medani, K., Gherbi, C. and Mabed, H. “Machine Learning Application in Software-Defined Networking Based Agricultural Internet of Things: A Systematic Literature Review,” *Cluster Computing*, 28 (10), p. 647, 2025.

[85] Maheshwari, A. and Panneerselvam, K. “Optimizing RPL for Load Balancing and Congestion Mitigation in IOT Network,” *Wireless Personal Communications*, 136 (3), pp. 1619–1636, 2024.

[86] Priyadarshi, R. “Exploring Machine Learning Solutions for Overcoming Challenges in IoT-Based Wireless Sensor Network Routing: A Comprehensive Review,” *Wireless Networks*, pp. 1–27, 2024.

[87] Anwer, R. W., Abrar, M., Salam, A. and Ullah, F. “TEAD: Trust-Enhanced Anomaly Detection Framework for Intrusion Detection in IoT-Enabled Wireless Sensor Networks (WSNs),” *Wireless Networks*, pp. 1–19, 2025.

[88] Isyaku, B., bin Abu Bakar, K., Yusuf, N. M., Abaker, M., Abdelmaboud, A. and Nagmeldin, W. “Software Defined Wireless Sensor Load Balancing Routing for Internet of Things Applications: Review of Approaches,” *Heliyon*, 2024.

https://doi.org/10.4314/njt.2025.4522

[89] Kapu, R. R. “Cross-Layer Optimization for End-to-End Performance in Enterprise Ecosystems,” *Journal of Multidisciplinary*, 5 (7), pp. 678–684, 2025.

[90] Raj, V. P. and Duraipandian, M. “An Energy-Efficient Cross-Layer-Based Opportunistic Routing Protocol and Partially Informed Sparse Autoencoder for Data Transfer in Wireless Sensor Network,” *Journal of Engineering Research*, 12 (1), pp. 122–132, 2024.

[91] Vijayakumar, K., Thirumaraiselvan, P., Sivakumar, B. and Seenuvasan, P. “Revolutionizing Data Transmission-A Comprehensive Review of Deep Learning-Based Routing Mechanism for 5G Wireless Sensor Networks,” in *2024 10th International Conference on Communication and Signal Processing (ICCSP)*, pp. 565–570, IEEE, 2024.

[92] Ahmed, S. F., Alam, M. S. B., Afrin, S., Rafa, S. J., Taher, S. B., Kabir, M. and Gandomi, A. H. “Towards a Secure 5G-Enabled Internet of Things: A Survey on Requirements, Privacy, Security, Challenges, and Opportunities,” *IEEE Access*, 2024.

[93] Hudda, S. and Haribabu, K. “A Review on WSN Based Resource Constrained Smart IoT Systems,” *Discover Internet of Things*, 5 (1), p. 56, 2025.

[94] Feng, J., Yu, T., Zhang, K. and Cheng, L. “Integration of Multi-Agent Systems and Artificial Intelligence in Self-Healing Subway Power Supply Systems: Advancements in Fault Diagnosis, Isolation, and Recovery,” *Processes*, 13 (4), p. 1144, 2025.

[95] Chen, R. “Optimizing Wireless Sensor Network Topology with Node Load Consideration,” *Virtual Reality & Intelligent Hardware*, 7 (1), pp. 47–61, 2025.

[96] Li, X., Zhou, L., Wang, Y., Hu, J. and Yu, D. “TCN-TransNet: A Hybrid Deep Learning Framework for Intelligent Fault Detection in Electrical Power Networks,” *Australian Journal of Electrical and Electronics Engineering*, 1, pp. 1–30, 2025.

[97] Oudah, A. Y., Alubady, R. and Shaker, L. M. “Recent Trends in Network Technologies: A Comprehensive Review,” *AUIQ Technical Engineering Science*, 2 (3), p. 5, 2025.

[98] Nejla, E., Saidani, K. and Besbes, M. “Overcoming the Integration Bottleneck: A Global Review of Renewable Energy and Grid Adaptation Strategies,” *International Journal of Sustainable Energy*, 44 (1), p. 2569922, 2025.

[99] Li, X., Zhou, L., Wang, Y., Hu, J. and Yu, D. “TCN-TransNet: A Hybrid Deep Learning Framework for Intelligent Fault Detection in Electrical Power Networks,” *Australian Journal of Electrical and Electronics Engineering*, 1, pp. 1–30, 2025.

[100] Oudah, A. Y., Alubady, R. and Shaker, L. M. “Recent Trends in Network Technologies: A Comprehensive Review,” *AUIQ Technical Engineering Science*, 2 (3), p. 5, 2025.

[101] Nejla, E., Saidani, K. and Besbes, M. “Overcoming the Integration Bottleneck: A Global Review of Renewable Energy and Grid Adaptation Strategies,” *International Journal of Sustainable Energy*, 44 (1), p. 2569922, 2025.

[102] Tawfeek, M. A., Alrashdi, I., Alruwaili, M., Jamel, L., Elhady, G. F. and Elwahsh, H. “Improving Energy Efficiency and Routing Reliability in Wireless Sensor Networks Using Modified Ant Colony Optimization,” *EURASIP Journal on Wireless Communications and Networking*, 2025 (1), p. 22, 2025.

[103] Jianping, Z. “Advancements in Network Softwarization and Optimization for VoIP and Wireless Sensor Networks in Smart Grids,” SSRN, 5296604, 2025.

[104] Nadanam, P., Kumaratharan, N. and Anousouya Devi, M. “Innovative Hybrid Framework for Routing and Clustering in Wireless Sensor Networks with Quantum Optimization,” *Cybernetics and Systems*, 1, pp. 1–36, 2025.

[105] Liu, N., Wang, J., Tao, F., Fu, Z. and Liu, B. “EDRP-GTDQN: An Adaptive Routing Protocol for Energy and Delay Optimization in Wireless Sensor Networks Using Game Theory and Deep Reinforcement Learning,” *Ad Hoc Networks*, 166, p. 103687, 2025.

[106] Sefati, S. S., Arasteh, B., Craciunescu, R. and Comsa, C. R. “Intelligent Congestion Control in Wireless Sensor Networks (WSN) Based on Generative Adversarial Networks (GANs) and Optimization Algorithms,” *Mathematics*, 13(4), p. 597, 2025.

[107] Anslam Sibi, S. and Sherly Puspha Annabel, L. “Network Lifetime Improvement in Wireless Sensor Networks Using Energy-

https://doi.org/10.4314/njt.2025.4522

Efficient Bat-Moth Flame Optimization Technique,” *Scientific Reports*, 15(1), p. 18065, 2025.

[108] Aleem, A. and Thumma, R. “Optimizing Energy Efficiency in IoT-Enabled Wireless Sensor Networks Using an Integrated EEKA-K-means Approach,” *International Journal of Intelligent Engineering & Systems*, 18(2), 2025.

[109] Shyamsundar, R. and Harshavarthan, M. “A Cluster Based Routing for Maximizing the Lifetime of Underwater Wireless Sensor Network Using Gravitational Search Algorithm,” *Results in Engineering*, 25, p. 104470, 2025.

[110] Chabira, C., Shayea, I., Nurzhaubayeva, G., Aldasheva, L., Yedilkhan, D. and Amanzholova, S. “AI-Driven Handover Management and Load Balancing Optimization in Ultra-Dense 5G/6G Cellular Networks,” *Technologies*, 13(7), p. 276, 2025.

[111] Cheruku, R., Yadav, A., Arukonda, S., Kodali, P., Boddu, V., Sureshbabu, E. and Kavati, I. “Wireless Sensor Networks Lifetime Optimisation Using Gaussian Integrated Bat Algorithm,” In *Role of Nature-Inspired Algorithms in Real-life Problems* (pp. 47–63). Singapore: Springer Nature Singapore, 2025.

[112] Zelani, S. K., Babu, D. N., Surendra, D. and Rahman, M. Z. U. “Energy-Efficient Ant Routing Algorithm for Optimized Path Selection Network Longevity in Wireless Sensor Networks,” *Telecommunications and Radio Engineering*, 84(2), 2025.

[113] Rajaram, V., Pandimurugan, V., Rajasoundaran, S., Rodrigues, P., Kumar, S. S., Selvi, M. and Loganathan, V. “Enriched Energy Optimized LEACH Protocol for Efficient Data Transmission in Wireless Sensor Network,” *Wireless Networks*, 31(1), pp. 825–840, 2025.

https://doi.org/10.4314/njt.2025.4522