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Research Article

Advancements and Challenges in Optimal node localization for Energy-efficient data transmission in IoT assisted Wireless Sensor Network: A Survey

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ABSTRACT

Optimal node localization is a key area of research focused on enhancing energy efficiency and data transmission accuracy within Internet of Things (IoT)-assisted Wireless Sensor Networks (WSNs). Despite advancements in localization methodologies, the field encounters significant challenges, including adapting to dynamic environmental conditions, managing energy constraints, and ensuring scalability across various network topologies. This survey provides a systematic review of around 30 research articles, focusing on the techniques used, challenges faced, and outcomes achieved in node localization for WSNs. By critically examining existing methods such as clustering, routing, and hybrid optimization approaches often integrated with machine learning this research highlights each strategy's strengths and limitations, providing insights into their applicability and effectiveness in real-world scenarios. Ultimately, the survey aims to guide future research toward developing more robust, adaptable, and energy-efficient localization solutions, contributing to enhanced network performance and prolonged sensor lifetimes in IoT-integrated WSN environments.

Keywords: Optimal node localization, Wireless Sensor Networks, clustering, routing and machine learning.

INTRODUCTION

Node localization has recently emerged as a significant technological advancement in the literature surrounding WSNs [1–3]. Effective node localization is essential for ensuring the accuracy and efficiency of these networks, which consist of numerous sensor nodes distributed over a geographic area to monitor specific regions of interest. In many WSN applications, the data generated by these sensors holds limited value without precise location information [4]. The challenge of determining the location of sensor nodes becomes even more critical when considering the limitations of WSNs, such as restricted power and wireless bandwidth [5]. Additionally, base stations that rely on receiving processed data from unidentified sources become ineffective in the absence of proper node localization, rendering the collected data useless [5]. As WSNs play an increasingly vital role in fields like industrial automation, area monitoring, and environmental measurements, accurate node localization becomes indispensable. This need for precise location estimation is especially crucial in the context of the rapid growth of the Internet of Things (IoT), where several methods, such as the Gaussian Elimination Method, have been proposed for determining a node's position [6]. Therefore, advancing localization techniques is paramount to enhancing the functionality and applicability of WSNs across various industries and applications [7].

WSNsare composed of numerous sensor nodes that facilitate the transmission of both small and large data packets. The evolution of electronic technology in WSNs has significantly improved the capabilities of these nodes, enhancing their roles in applications such as system control, tracking, environmental monitoring, and security [8]. A key aspect of these networks is node localization, which plays a crucial role in enabling effective communication and data processing in various network applications. However, WSNs face persistent challenges, particularly related to node localization and energy consumption [9-11]. The limited battery life of sensor nodes constrains their processing and computational abilities, making efficient energy management essential for network performance. Sensor nodes consume energy not only for sensing and processing data but also for storing and transmitting packets. Additionally, the network employs various routing protocols that can be classified as either flat or hierarchical. In flat protocols, all nodes are considered equal and communicate directly with neighboring nodes to transmit data to the destination. In contrast, hierarchical protocols assign distinct roles to nodes, optimizing communication and energy usage by organizing nodes into layers with varying responsibilities.

In WSNs, standard sensor nodes send their data to a CH, which is responsible for aggregating and compressing the information before forwarding the data packets to the BS. Because of these additional tasks, cluster head nodes use significantly more energy than other sensor nodes in the network [12-14]. In WSNs, data flows from the source node to the base station with the help of a cluster head, which generally has more residual energy than its cluster members. Over the past decade, numerous studies on node localization in WSNs have shown that the coordinates of unknown sensor nodes can be determined by one or more nodes equipped with GPS. Clustering is a widely used strategy in WSNs that promotes energy efficiency by organizing the network into distinct regions cluster heads and member nodes [15]. Each cluster is managed by a cluster head, which gathers data from its member nodes, compiles it into packets, and sends it to the sink node. However, since cluster heads consume energy more rapidly, it is often necessary to rotate the cluster head role among the nodes. This rotation helps avoid the early depletion of any single node's energy and promotes more balanced energy consumption across the network, ultimately extending the system's overall lifespan [15-18].

This survey seeks to identify and assess various methods for optimal node localization in IoT-assisted WSNs, with an emphasis on classification categories such as clustering techniques, routing strategies, clustering-based routing, and their integration with machine learning optimization for enhanced energy-efficient data transmission.By analyzing assessment metrics, practical benefits, and drawbacks, this research explores the unique challenges posed by each method, including data and energy constraints, computational complexity, and adaptability to diverse network conditions. Based on an extensive review of approximately 30 studies, the survey categorizes and assesses methodologies, highlights the specific techniques and optimizations used, and examines the contextual limitations of each.

This discussion is organized into specific sections that systematically review the literature on node localization for IoT-assisted WSNs. Section 2 presents an article selection process. Section 3 summarizes key methodologies, evaluation metrics, achievements, and limitations encountered in existing studies. Section 4 provides an in-depth evaluation of the effectiveness of these metrics in achieving optimal localization and minimizing energy consumption. Section 5 identifies research gaps uncovered during the review, highlighting areas for further development. Finally, Section 6 concludes the survey with a summary of significant findings and proposed directions for future research to improve energy efficiency and localization accuracy in WSNs.

2. Article selection process: The following section describes the process used to select articles for this extensive literature review on optimal node localization for energy-efficient data transmission in IoT-enabled WSNs. By systematically identifying and evaluating key studies, this review highlights various localization techniques and optimization strategies that are currently applied to enhance energy efficiency and transmission accuracy in WSNs.The section clarifies the selection criteria and research processes, laying a foundation for understanding the range of challenges, innovations, and advancements in node localization within IoT-integrated WSNs

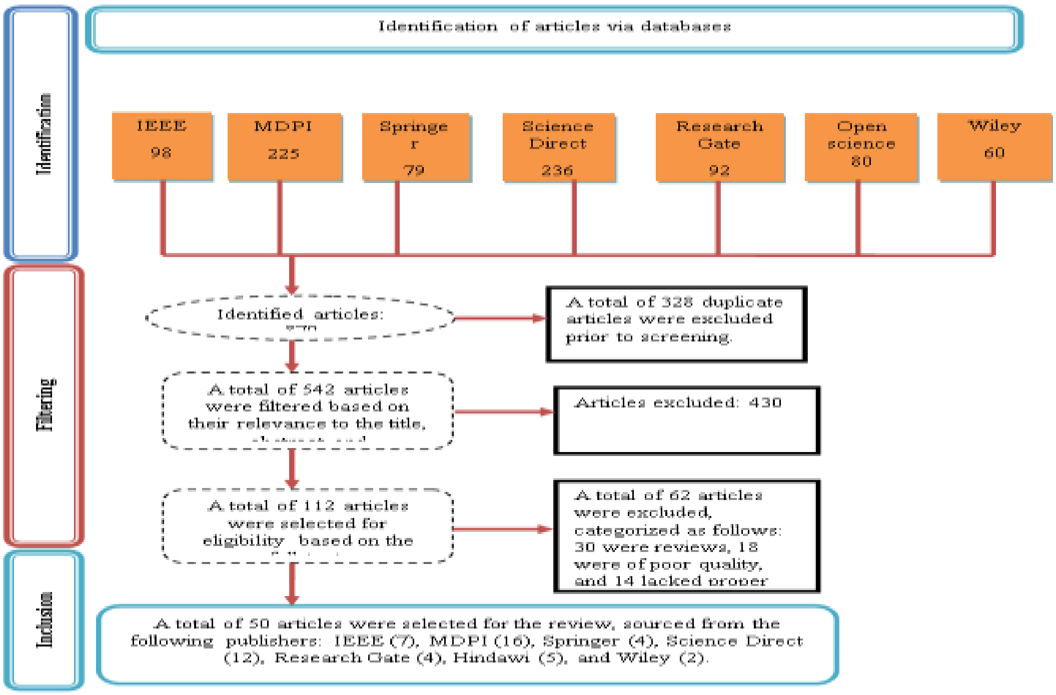

Figure 1: Schematic representation for the article selection process

This review adopts a systematic literature review (SLR) methodology, adhering to the PRISMA guidelines to ensure a rigorous, transparent, and reproducible process for study selection and evaluation. As depicted in Figure 1, the PRISMA-based review process outlines each stage of selecting relevant studies, specifically focusing on optimal node localization techniques for energy-efficient data transmission in IoT-assisted WSNs. To begin, a comprehensive search of relevant databases was conducted, which yielded an initial collection of 870 documents published between 2020 and 2024. This time frame was chosen to focus on the latest advancements in node localization and energy efficiency in IoT-integrated WSNs, ensuring that the review captures the most up-to-date research trends in these fields. The documents included a variety of studies, from foundational theories to emerging innovations in the application of energy-efficient data transmission techniques. Each article was first screened for relevance based on its title and abstract. Following this, a more detailed evaluation was performed on the full text of the articles. This process ensured that only studies aligning with the review's specific focus on node localization and energy efficiency in IoT-assisted WSNs were considered for inclusion. Exclusions were made for review articles, as they do not present original research; studies deemed to be of poor quality, which failed to meet basic research standards; and papers lacking sufficient analysis or details on the techniques used. In total, 62 articles were excluded at this stage, with 30 studies selected for in-depth analysis. The PRISMA flow diagram serves as a visual representation of the entire search and selection process. It outlines the number of records identified through database searches, the number of studies included in the final review, and the reasons for excluding articles. This diagram is a crucial element in maintaining transparency, providing readers with a clear understanding of how the final set of articles was determined. By following a structured methodology, this review ensures that the selected studies meet high standards of research quality and contribute valuable insights into the optimization of node localization for energy-efficient data transmission in IoT-assisted WSNs. The goal is to capture the current state of research, identify prevailing trends, and highlight gaps or underexplored areas in the field. These insights are essential for advancing the field of IoT-assisted WSNs, paving the way for the development of more energy-efficient localization techniques that can improve the sustainability and performance of future networks.

A. Taxonomy of Optimal Node Localization Techniques for Energy-Efficient Data Transmission in IoT-Assisted WSNs:

Figure 2 presents a taxonomy diagram that categorizes various methods used for optimal node localization in IoT-assisted WSNs, aimed at enhancing energy efficiency in data transmission. This diagram includes clustering, routing, and hybrid approaches, as well as techniques integrating machine learning (ML) for optimization. It provides a comprehensive overview of these methods and their specific applications in localization, demonstrating how these approaches intersect to address challenges such as energy conservation, accuracy, and scalability in real-world WSN scenarios. This taxonomy highlights the range of strategies available and guides researchers in selecting suitable localization techniques for specific IoT-WSN applications.

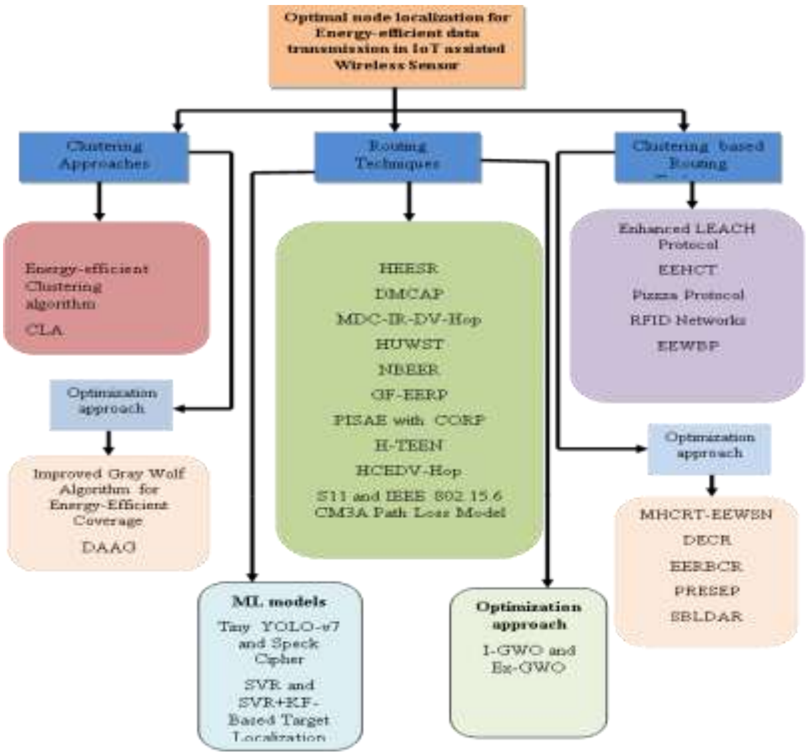

Figure 2: Taxonomy diagram of optimal node localization techniques

i) Clustering approach:

Yogesh Patidar et al. [22] proposed an energy-efficient clustering and data transmission algorithm tailored for heterogeneous WSNs, focusing on minimizing energy consumption throughout both the cluster formation (setup phase) and data transmission (steady-state phase). The protocol introduces a dynamic sectoring method that divides the global network into local zones, enhancing the accuracy and effectiveness of cluster head selection. This approach demonstrated notable improvements in energy efficiency and data transmission performance compared to existing protocols. However, challenges persist in managing the dynamic sectoring process, particularly in ensuring precise time synchronization across nodes, which could impact the protocol's scalability and robustness in large-scale networks. Hitesh Mohapatra et al. [7] introduced the CLOCK-Localization Approach (CLA), an energy-efficient topological localization technique for WSNs designed to extend the network's lifetime. The CLA leverages a CLOCK pattern-based sensor deployment strategy, which significantly reduces the need for frequent reclustering and iterative cluster head (CH) selection. By assigning dual roles to selected cluster heads as both CHs and vice-cluster heads, the protocol minimizes energy consumption and overhead, providing a more sustainable solution. While CLA outperforms traditional localization methods in energy efficiency, its scalability may become an issue in large networks, and maintaining optimal CH roles in dynamic environments presents a potential drawback that could affect long-term performance. Antar Shaddad Hamed Abdul-Qawy et al. [15] proposed the TESEES (Threshold Enabled Scalable and Energy Efficient Scheme), a zone-based, event-driven protocol designed to optimize energy consumption in large-scale heterogeneous WSNs while extending the lifespan of battery-powered nodes. TESEES stands out by achieving a 29% improvement in energy savings, a 68% increase in network lifetime, and a 26% reduction in transmitted data when compared to the conventional SEES protocol. Additionally, it reduces the average energy consumption per round by 36%. Despite its impressive performance, TESEES faces challenges related to the complexity of its multi-stage aggregator election mechanism. Furthermore, its reliance on energy-harvesting relay nodes may limit its effectiveness in certain scenarios, especially when energy harvesting is not consistently reliable or sufficient.

ii) Clustering approach+optimization:

Maria Hanif et al. [10] presented a hybrid approach, Distance and Angulation-based A Gglomerative Clustering (DAAG), aimed at optimizing sink node placement in Wireless Body Area Networks (WBANs). The DAAG method first utilizes a Distance and Angulation-based k-Means clustering technique to group the WBAN sensors based on their proximity and angular orientation. Subsequently, Agglomerative Clustering is applied to determine the most optimal locations for the sink nodes. This two-step process significantly enhances the overall network performance, demonstrating a marked improvement over existing methods. Specifically, DAAG achieves an energy consumption of just 1.51%, substantially reducing energy usage, while also improving localization accuracy by 0.36 meters. Additionally, the approach outperforms traditional clustering algorithms in terms of reducing latency and minimizing the packet error rate (PER), making it a highly efficient and reliable solution for optimizing sink node placement in WBANs. However, the hybrid approach may introduce complexity and require careful parameter tuning to maintain optimal performance in diverse WBAN configurations Runliang jia and haiyu zhang [2] presented an energy-efficient coverage method for WSN using an improved gray wolf algorithm to optimize sensor node deployment. The advantages include significant improvements in network coverage, achieving a 5.08% increase in coverage rate compared to other algorithms, and effective performance under 30-dimensional conditions. However, challenges may arise from the algorithm's complexity, which could require more computational resources, and difficulties in adapting to dynamic environments where sensor nodes must adjust to changes or failures. Salem Jeyaseelan WR et al. [6] introduced the Improved Grey Wolf Optimization-Based Node Localization Approach (IGWONL-UWSN) to address the complex challenges of node localization in Underwater WSN (UWSNs). This innovative approach leverages a hunting-inspired optimization technique, enhanced by a Dimension Learning-based Hunting (DLH) search process, to significantly improve both convergence speed and localization accuracy. This method stands out for its exceptional performance metrics, offering more precise localization compared to traditional methods. Its ability to efficiently navigate the unique challenges of underwater environments such as signal attenuation and unpredictable conditions makes it particularly well-suited for critical applications like underwater surveillance, environmental monitoring, and oceanographic research. By optimizing the localization process, IGWONL-UWSN ensures more reliable and accurate positioning of nodes, which is essential for the robustness and effectiveness of UWSNs in real-world scenarios. However, challenges include sensitivity to dynamic underwater conditions, potential computational complexity, and limitations in real-time adaptability, which may hinder practical implementation.

iii) Routing approach: A. Roshini and K.V.D. Kiran [13] introduced the Hierarchical Energy-Efficient Secure Routing protocol (HEESR) for remote health monitoring using Wireless Body Area Networks (WBANs). HEESR classifies nodes into direct and relay types, depending on their energy levels and traffic priorities, to optimize data transmission, especially for patients in critical conditions. The advantages of this model include a 6% reduction in energy consumption, 92% throughput, and 93% security, achieved through Huffman encoding for data compression and asymmetric encryption. However, challenges include the complexity of real-world implementation and the need for extensive validation in diverse scenarios to ensure consistent performance and reliability. Rajasoundaran Soundararajan et al. [17] proposed the Deep Learning-based Multi-Channel Learning and Protection Model (DMCAP) for Wireless Underground Sensor Networks (WUGSNs), aimed at improving data transmission from underground sensors that monitor environmental parameters. The model demonstrates a 10% to 15% performance improvement in throughput, reduced retransmission rates, and lower energy consumption compared to existing methods. However, it struggles with accurately identifying impacts from channel issues and malicious attacks, indicating a need for further refinement in real-time adaptability and robustness against security threats. Rahma Gantassi et al. [14] proposed the Mobile Data Collector-Improved Recursive Distance Vector-Hop (MDC-IR-DV-Hop) protocol to optimize routing in large-scale WSN (LS-WSNs) and high sensor node density networks (HSND-WSNs). By incorporating a mobile data collector (MDC), the protocol improves the quality of service (QoS) through more efficient data collection and routing optimization. This approach offers significant benefits, including enhanced energy efficiency and reduced communication delays when compared to traditional protocols. However, the MDC implementation can be complex and may require substantial adaptation to various network topologies, posing potential challenges. Meanwhile, Jiasen Zhang et al. [11] introduced the Hierarchical Underwater Wireless Sensor Transmission (HUWST) framework, aimed at improving energy efficiency and balancing energy consumption across sensor nodes deployed at varying water depths in UWSNs. This framework seeks to address the unique challenges of energy management in underwater environments, ensuring prolonged network operation and optimized resource usage. The approach demonstrates significant improvements in energy efficiency and balanced consumption across nodes, outperforming baseline schemes in simulations. However, challenges include the complexity of the NIP formulation and the computational overhead of the alternating direction method of multipliers (ADMM) algorithm, which may affect real-time implementation in dynamic underwater settings. Sayyed Mudassar Shah et al. [18] introduced the Neighbor-Based Energy-Efficient Routing (NBEER) protocol tailored for UWSNs. This protocol addresses critical challenges such as high power consumption, limited network lifetime, and complex topology management inherent in underwater environments. Through simulations, NBEER demonstrates significant advantages over existing protocols like Co-UWSN and Cooperative Energy-Efficient Routing (CEER). It notably reduces energy consumption, enhances packet delivery ratios, extends network lifetime, and lowers end-to-end delay. While these improvements mark substantial progress, implementing Neighbor Hop Node (NHN) selection algorithms can add complexity, and adapting to dynamic underwater conditions may increase overhead. This points to a potential need for adaptive mechanisms to handle environmental variability effectively, ensuring robust performance under diverse underwater scenarios. Prasanta Pratim Bairagi et al. [19] proposed the Geographic Forwarding Energy Efficient Routing Protocol (GF-EERP) for WSNs, building on the Geographic Energy Aware Routing (GEAR) protocol. GF-EERP optimizes network performance and extends network longevity by strategically incorporating geographic forwarding with energy efficiency techniques. This approach further refines energy consumption patterns within the network, promoting sustainable operation in energy-constrained WSN environments. The key innovations include node categorization, a new method for selecting region heads, and a multi-hop communication strategy that eliminates dead nodes. While GF-EERP provides better energy efficiency and extended network life, its complexity in node categorization and region head selection may introduce overhead and slow down responses in dynamic environments. Vivek Pandiya Raj and M. Duraipandian [23] developed an advanced model integrating the Partially Informed Sparse Autoencoder (PISAE) with a Cross-layer Opportunistic Routing Protocol (CORP) to achieve energy-efficient communication in WSNs. This model aims to reduce unnecessary data transmission, thereby extending the lifespan of sensor nodes. Its key benefits include improved quality of service (QoS), high throughput (1.0 Mbps), low packet loss (1.5%), extended network lifetime (6100 rounds), and reduced energy consumption (30.35 mJ). However, challenges in implementation and adaptability in diverse network environments may arise. S. Ramesh et al. [25] introduced a robust model for Mobile Sensor Networks (MSNs) designed to address key challenges such as coverage, connectivity, and energy efficiency in dynamic environments. The model incorporates a Multi-Path Link Routing Protocol (MLRP) alongside a Hybrid Threshold-sensitive Energy Efficient Network (H-TEEN) protocol to support secure, energy-efficient communication among mobile sensors. By dynamically optimizing node-to-node distances, the model achieves both reliable data transmission and effective energy conservation, adapting to changes in network topology to ensure sustained performance in highly mobile and variable conditions. The model incorporates recurrent neural networks (RNN) for signal classification and malicious node detection, enhancing network security. The key advantages include prolonged network lifespan through effective energy balancing and improved security. However, the model may face challenges related to the complexity of implementing multi-path routing and the need for real-time processing with RNNs, which could impact performance in highly mobile situations. Muhammad Fawad et al. [8] proposed the Hop-Correction and Energy-Efficient DV-Hop (HCEDV-Hop) algorithm, designed to significantly improve localization accuracy and reduce energy consumption in WSNs. Building on the standard DV-Hop method, HCEDV-Hop introduces three crucial enhancements: first, it refines single-hop distance measurements using Received Signal Strength Indicator (RSSI) values for more accurate distance estimation; second, it adjusts average hop distances by comparing actual and estimated distances, thus accounting for network variations; and third, it employs a least-squares approach to further improve location estimation accuracy. The algorithm achieves an average localization accuracy improvement of 81.36% compared to basic DV-Hop, while reducing energy consumption by 28%. However, its complexity and reliance on RSSI may lead to scalability challenges and errors caused by environmental factors affecting signal strength. Neha Arora et al. [9] presented a method to optimize the placement of a central node in WBANs by utilizing the antenna's Reflection Coefficient (S11) alongside the IEEE 802.15.6 CM3A path loss model. The approach improves communication efficiency and data transmission reliability through the optimal positioning of the central node.However, disadvantages include the reliance on a controlled laboratory environment, which may not reflect dynamic real-world conditions, and the specific antenna characteristics that could limit the findings' applicability to other designs.

iv) Routing approach+optimization:

Amir Seyyedabbasi et al. [3] introduced two innovative energy-efficient routing approaches for WSNs and decentralized IoT systems, leveraging the Incremental Grey Wolf Optimization (I-GWO) and Expanded Grey Wolf Optimization (Ex-GWO) algorithms. These methods are designed to optimize path finding by improving route selection and balancing energy consumption across network nodes. These methods offer significant advantages, including the adaptive ability to find optimal paths of varying lengths between source and destination nodes, resulting in cost-effective routing solutions. Despite these benefits, the methods face challenges, particularly due to the complexity of the algorithms, which may demand substantial computational resources. Additionally, the lack of a pre-existing dataset for validation limits the evaluation of the model’s performance, as it was only tested in a simulation environment.

v) Routing approach+ ML models:

Jahir Pasha Molla et al. [16] presented two range-free target localization schemes for indoor WSNs one that uses a basic Support Vector Regression (SVR) model and another that integrates SVR with a Kalman Filter (KF), called the SVR+KF algorithm. These schemes offer significant advantages, including reduced energy consumption compared to traditional trilateration methods, as they require fewer measurements for target localization. Specifically, the SVR+KF algorithm enables accurate location determination using only three Received Signal Strength Indicator (RSSI) measurements, making it an efficient and energy-saving solution for indoor WSNs.Simulation results show that the SVR-based models, particularly with linear and polynomial kernel functions, significantly outperform trilateration-based schemes in localization accuracy. However, the models require careful kernel selection and tuning, as their performance may vary based on the specific indoor conditions. Osama a. khashan et al. [21] introduced an energy-efficient protection model for WMSN that utilizes a lightweight Tiny YOLO-v7 framework for dynamic object identification in images, reducing unnecessary data transmission. The model integrates the Speck cipher for encrypting detected objects and employs a scrambling method for image pixel shuffling, along with a key management scheme for secure communication among nodes. The proposed approach significantly decreases node power consumption by about 49% and enhances network lifetime by 50% compared to conventional methods. However, it may encounter challenges such as the need for continuous security updates and potential processing power limitations in resource-constrained environments.

vi) Clustering based routing approach:

Bhukya Suresh and G. Shyama Chandra Prasad [5] presented a LEACH (Low-Energy Adaptive Clustering Hierarchy) protocol designed to improve the stability and energy efficiency of CH selection in WSNs within the IoT. The model advantages include increased energy efficiency, extended network longevity, and improved communication quality, as shown in simulation results. However, potential disadvantages include the complexity of the Rank-based selection mechanism, which may lead to higher computational overhead, and challenges in adapting the model to various network topologies and real-world conditions. Sandip K. Chaurasiya et al. [24] proposed an Energy-Efficient Hybrid Clustering Technique (EEHCT) for IoT-based Heterogeneous ESN (HWSN). This approach focuses on reducing energy consumption during the cluster formation process while ensuring an even distribution of the network load, ultimately improving the overall network lifetime. By combining dynamic and static clustering strategies, EEHCT reduces the energy costs associated with frequent cluster reformation, achieving a 90.27% improvement in network lifetime compared to existing protocols under various conditions. However, challenges remain in terms of implementation complexity and the need for further optimization in highly dynamic environments to maintain efficiency at varying levels of heterogeneity. Similarly, Sara Nasirian et al. [26] introduced Pizzza, a cluster-based hierarchical routing protocol aimed at enhancing energy efficiency and extending the lifetime of WSNs. Pizzza minimizes energy consumption by constructing minimum spanning trees within sector-shaped clusters and limiting cluster head roles to eligible nodes. This approach reduces reverse data flow to the base station and facilitates direct transmission to neighboring nodes. As a result, Pizzza achieves a 65.52% increase in network lifetime and a 77.05% improvement in residual energy compared to existing protocols. However, it may face challenges related to the complexity of cluster formation and maintenance, potentially impacting its scalability and adaptability in dynamic environments. M. Thurai pandian et al. [28] introduced a dynamic cluster head selection model for large-scale RFID networks using Radio Frequency Identification (RFID) technology. It employs a clustering approach to enhance scalability and performance by managing the connectivity and power of RFID readers. The system is capable of supporting up to a thousand nodes with 13 leaders, achieving a high success rate of 97.8%. It demonstrates a low error rate of 2.64% and operates with a latency of 36.91 seconds, ensuring efficient performance across a large-scale network.However, potential disadvantages include the complexity of Fuzzy Logic implementation and challenges in communication and energy management as the network scales. Puneet Kaur et al. [29] introduced the Energy-Efficient Weighted-Based Protocol (EEWBP) for enhancing the performance of WSN in forest applications such as fire detection and battlefield surveillance. The model employs a composite weighted metric that incorporates factors like node degree, residual energy, neighbor count, average flying speed, and trust value to facilitate effective cluster formation and node scheduling. This clustering approach reduces energy consumption while extending the coverage lifetime of sensor nodes. However, potential disadvantages may include increased complexity in implementation and the need for accurate measurement of the weighted metrics for optimal performance.

vii) Clustering based routing approach +optimization:

Sweta Kumari Barnwa et al. [4] introduced the Metaheuristic Cluster-Based Routing Technique for Energy-Efficient WSN (MHCRT-EEWSN), designed to improve energy efficiency and prolong the lifespan of WSNs within the IoT. This model utilizes Whale Moth Flame Optimization (WMFO) to optimize clustering, focusing on minimizing intra-cluster and inter-cluster distances, balancing energy consumption, and enhancing overall network performance. For routing, it employs the improved African buffalo optimization (IABO) algorithm, which optimizes routes based on residual energy and distance. This model includes enhanced energy efficiency and performance in simulations compared to other methods. However, challenges include the complexity of the algorithms, which may increase computational demands, and potential difficulties in real-world implementation due to varying environmental conditions and network configurations. Muhammad Yeasir Arafat et al. [12] introduced a distributed, energy-efficient two-hop-based clustering and routing protocol (DECR) for wearable IoT (WIoT)-enabled WBAN. The protocol employs a modified GWO algorithm to optimize cluster head selection and routing, taking into account factors such as node connectivity and residual energy. Furthermore, an analytical model is incorporated to determine the optimal number of clusters, effectively minimizing both transmission distances and energy consumption. The results highlight DECR's superior performance over existing clustering and routing protocols across multiple metrics, although its implementation may entail additional complexity and overhead in managing neighbor information. In a similar approach, Haseena Gul et al. [20] proposed the Energy-Efficient Regional Base Cooperative Routing (EERBCR) protocol, designed to enhance the network lifetime of UWSNs by optimizing energy consumption. EERBCR partitions the network into 12 regions and employs four mobile sinks, each covering three regions along predefined paths, improving energy efficiency and extending the operational lifespan of the network. Sensor nodes remain in sleep mode until activated by a "hello" message from an incoming sink. Once the sink departs, it broadcasts a message to return the nodes to sleep mode. Simulation results show that EERBCR outperforms existing protocols in terms of energy efficiency.However, challenges include dependency on mobile sinks, which could restrict coverage if not managed effectively, and the necessity for precise path planning to ensure comprehensive region monitoring. Sarvesh Kumar Sharma and Mridul Chawla [27] presented a hybrid data routing algorithm, the Particle Swarm Optimized Residual Energy-based Stable Election Protocol (PRESEP), designed to enhance energy efficiency in WSNs within the IoT. This algorithm integrates swarm optimization techniques with energy-efficient heuristics to enhance data routing in heterogeneous WSNs. PRESEP offers several advantages, including extended network lifetime, a higher number of active nodes, and reduced energy consumption by minimizing the frequency of Cluster Head (CH) selections. However, its implementation may be complex due to the hybrid approach, and calibration is needed to ensure optimal performance across varying network conditions. In a similar vein, Nilabar Nisha U et al. [30] introduced the Score-Based Link Delay Aware Routing (SBLDAR) protocol, designed to enhance energy efficiency and minimize data transmission collisions in WSNs. The protocol incorporates a trust-based mechanism to detect malicious nodes, while leveraging a fuzzy-based Modified Sun Flower Optimization (FMSFO) algorithm for optimal cluster head selection. By improving energy efficiency and network performance, SBLDAR significantly extends the network's lifetime compared to existing protocols. However, the approach faces challenges such as the complexity associated with multi-channel implementation and the reliance on accurate trust evaluations for ensuring optimal protocol performance.

3. Analysis of Optimal Node Localization Techniques for Energy-Efficient Data Transmission:

This survey explores recent advancements in optimizing node localization techniques within IoT-assisted WSNs to achieve energy-efficient data transmission. It examines the achievements, advantages, methodologies, and challenges of various approaches, focusing on clustering, routing, and hybrid strategies. Additionally, the survey highlights the integration of machine learning models, which play a significant role in enhancing localization accuracy and minimizing power consumption in WSNs.The analysis emphasizes the benefits of these techniques, including enhanced network lifespan, reduced energy usage, and reliable data transmission, while also addressing persistent challenges like scalability, adaptability in dynamic environments, and limited resources. By providing a comprehensive assessment, this section underscores how these methodologies impact WSN performance, revealing critical insights into their applicability and limitations in real-world IoT deployments.

Table 1:A summarized analysis of optimal node localization for energy-efficient data transmission in IoT-assisted WSNs

Author	**Achievements**	**Advantages**	**Method**	**Challenges**
Mohammed Rizwanullah et al. [1]	It achieves superior energy efficiency, consistently recording lower Average Energy Consumption (AECN) across different node counts, with a notable AECN of 5.35 J at 250 nodes, compared to higher values in protocols like NSSROP, PRRP, PDORP, DSR, and LEACH.	Reduced energy usage Lower transmission delays Higher throughput Extended network lifetime	HMSFO-EARS	• Complexity of algorithm integration leading to increased computational overhead • Varying density of sensor nodes may affect optimal path availability and overall network performance
Runliang jia and haiyu zhang [2]	IGWO has proven highly effective in optimizing WSN coverage, achieving 100% coverage of monitoring points with a more energy-efficient approach compared to other methods. In a scenario with 40 nodes, IGWO increased the coverage rate by 5.08%.	Significant improvement in network coverage	Improved gray wolf algorithm	• Complexity of the algorithm may require more computational resources • Difficulty in adapting to dynamic environments where sensor nodes need to adjust to changes or failures
Amir Seyyedabbasi et al. [3]	The proposed methods outperformed other algorithms in network lifetime, alive node ratio, and packet delivery, showing the highest efficiency. They achieved low routing overhead (6.03% and 7.18%, respectively) and higher throughput, demonstrating their effectiveness in energy-efficient routing.	The ability to adaptively identify optimal paths of any length between source and destination nodes.	I-GWO and Ex-GWO	Complexity of algorithms may require substantial computational resources
Sweta Kumari Barnwa et al. [4]	The MHCRT-EEWSN model achieved a minimal end-to-end delay of 1.36 ms and a peak packet delivery ratio of 99.53% with 100 nodes, while also demonstrating a maximum throughput of 0.9969 bps and a network lifetime of 5442 rounds.	Improved energy efficiency and extended lifespan	MHCRT-EEWSN	Potential difficulties in real-world implementation due to varying environmental conditions and network configurations
Bhukya Suresh a and G. Shyama Chandra Prasad	The enhanced LEACH protocol achieved a packet delivery ratio of	Increased energy efficiency and extended network longevity	Enhanced LEACH Protocol	Complexity of the rank-based selection mechanism may result in

[5]	93.75% and reduced energy consumption to 3.1 J, outperforming AWFCC and CARF. It also minimized end-to-end delay to 0.17 ms for 50 nodes and maintained a throughput of 216 kbps.		with Rank-based Cluster Head Selection	higher computational overhead
Salem Jeyaseelan WR et al. [6]	The IGWONL-UWSN method significantly enhances the number of localized nodes (LN) and localization efficiency (LE) compared to existing techniques, achieving LN values of 163 and 198 with 10 and 50 anchors, respectively, and minimum LE values of 0.181 and 0.053.	Enhanced performance metrics for node localization	IGWONL-UWSN	• Potential computational complexity • Limitations in real-time adaptability may hinder practical implementation
Hitesh Mohapatra et al. [7]	The CLA reduces energy consumption by 21%, extends network lifetime significantly, and delivers 154,846 packets, outperforming BCDCP and LEACH-C.	Enhances energy efficiency and prolongs network lifetime	CLA	• Scalability challenges with larger networks • Difficulties in maintaining optimal CH roles in dynamic environments may impact performance
Muhammad Fawad et al. [8]	HCEDV-Hop enhances localization accuracy by an average of 81.36% outperforms benchmark schemes in terms of overall performance.	Achieves an 81.36% improvement in localization accuracy over basic DV-Hop	HCEDV-Hop	Reliance on RSSI can introduce errors due to environmental factors affecting signal strength
Neha Arora et al. [9]	Identified the chest as the ideal location for the central node, resulting in significantly lower return loss, normalized S11, VSWR, and average path loss, alongside higher energy efficiency and better communication quality compared to other placements (arm, thigh, and head).	Improved communication efficiency and data transmission reliability through optimal central node placement.	Optimal central node placement using Reflection Coefficient (S11) and IEEE 802.15.6 CM3A path loss model	Specific antenna characteristics could limit applicability to other designs.
Maria hanif et al. [10]	DAAG demonstrated superior performance with only 1.51% energy consumption, reduced latency, and improved	High accuracy of 0.36 m.	DAAG	Requires careful parameter tuning to maintain optimal performance in diverse WBAN configurations.

	localization accuracy of 0.36 m, outperforming various machine learning and optimization approaches			
Jiasen Zhang et al. [11]	The total overhead of the optimal mechanism increased at a slower rate compared to TAC and TDBS, showing reductions of 25% and 40%, respectively, at a sensor node count of 15.	Notable improvements in energy efficiency and a more balanced energy consumption across sensor nodes.	HUWST	• Complexity of the NIP formulation may pose challenges. • Computational overhead of the ADMM algorithm could affect real-time implementation in dynamic underwater settings.
Muhammad yeasir Arafat et al. [12]	The proposed DECR protocol enhanced the packet delivery ratio (PDR) by 30%, reduced the average end-to-end delay by 25%, and lowered control overhead by 30%. It also extended cluster lifetime by 50%, decreased energy consumption by 35%, maintained 20% more residual energy, and increased the number of active nodes by 25%.	Reduces transmission distances and energy consumption through optimal cluster selection.	DECR	Potential overhead associated with the analytical model used to determine the optimal number of clusters.
A. Roshini and K.V.D. Kiran [13]	The HEESR protocol improved energy consumption by 6%, achieved a throughput of 92%, and enhanced security to 93%, significantly reducing the packet drop rate and ensuring timely data delivery.	• Improved energy consumption with a 6% reduction. • High throughput	HEESR	Need for extensive validation across varied scenarios to ensure consistent performance and reliability.
Rahma gantassi et al. [14]	The MDC-IR-DV-Hop protocol accurately locating sensor nodes, reducing data collection delays, and improving energy efficiency and reliability compared to various existing protocols.	• Improved energy efficiency. • Reduced delays in data collection and routing.	MDC-IR-DV-Hop	Need for extensive adaptation to various network topologies.
Antar Shaddad Hamed Abdul-Qawy et al. [15]	TESEES resulted in a total energy saving of 29%, a 68% extension in lifetime, with an	• Improvement in energy savings • Extension in network lifetime.	TESEES	• Complexity of the multi-stage aggregator election mechanism. • Potential limitations from reliance

	average energy consumption decrease of 36% per round.			on energy-harvesting relay nodes.
Jahir Pasha Molla et al. [16]	The proposed SVR-based target localization methods demonstrated significant improvements in localization accuracy compared to trilateration, achieving a reduction in average RMSE by 99% with SVR+KF using a polynomial kernel, and by 68% with the linear kernel.	Significant improvement in localization accuracy, especially with linear and polynomial kernel functions.	SVR+KF algorithm	• Requires careful kernel selection and tuning. • Performance may vary based on specific indoor conditions.
Rajasoundaran Soundararajan et al. [17]	A performance improvement of 10% to 15% over existing systems.	• Improvement in throughput. • Reduced retransmission rates. • Lower energy consumption compared to existing methods.	DMCAP	Difficulty in accurately identifying impacts from channel issues and malicious attacks.
Sayyed Mudassar Shah et al. [18]	NBEER significantly increased end-to-end delay while reducing energy consumption compared to existing protocols.	• Prolongs network lifetime.	NBEER	Potential need for adaptive mechanisms to address dynamic underwater conditions, increasing overhead.
Prasanta Pratim Bairagi et al. [19]	GF-EERP demonstrated superior network throughput compared to existing protocols, with values ranging from 656 to 6512 packets across various network sizes (20 to 100 nodes).	• Improved energy efficiency. • Extended network lifespan.	GF-EERP	• Potential overhead and slower responses in dynamic environments.
Haseena Gul et al. [20]	The EERBCR protocol improved throughput by approximately 19% and reduced energy consumption by 23%, significantly extending the network lifetime of UWSNs.	• Extends network lifetime of UWSNs. • Optimizes energy consumption. • Outperforms existing protocols in energy efficiency.	EERBCR Protocol	• Dependency on mobile sinks, which may restrict coverage if not managed effectively. • Requires precise path planning for comprehensive region monitoring.
Osama a. khashan et al. [21]	The proposed Energy-Efficient Protection Model for WMSNs reduces node power consumption by 49% and improves network lifetime by 50% compared to traditional encryption methods.	• Reduces unnecessary data transmission, improving energy efficiency. • Decreases node power consumption. • Enhances network lifetime	Energy-Efficient Protection Model	• Requires continuous security updates. • Potential processing power limitations in resource-constrained environments.

Yogesh Patidar et al. [22]	Showed increased overall throughput due to prolonged network lifetime, surpassing existing protocols by 30% in throughput metrics	• Improves energy efficiency during cluster formation and data transmission. • Enhances data transmission effectiveness compared to existing protocols.	GLCHS	• Challenges in managing dynamic sectoring. • Ensuring time synchronization among nodes may be difficult.
Vivek Pandiya Raj a and M. Duraipandian [23]	Network Lifetime: 6100 rounds. End-to-End Delay: 1.5 seconds. Energy Consumption: 30.35 mJ.	• High throughput • Minimal packet loss • Prolonged network lifetime • Lower energy consumption	PISAE with CORP	• Implementation complexity. • Adaptability challenges in diverse network environments.
Sandip k. chaurasiya et al. [24]	Network Lifetime Improvement: Up to 90.27% gain compared to state-of-the-art schemes.	• Minimizes energy consumption in cluster formation. • Evenly distributes network load. • Enhances network lifetime	EEHCT	• Implementation complexity. • Need for optimization in highly dynamic environments to maintain efficiency across varying heterogeneity levels.
S. Ramesh et al. [25]	Extends network lifespan by balancing energy based on residual energy and energy density.	• Prolongs network lifespan through effective energy balancing. • Enhances network security via signal classification and malicious node detection.	MLRP and H-TEEN	• Complexity in implementing multi-path routing. • Requires real-time processing with RNNs, which may affect performance in highly mobile situations.
Sara nasirian et al. [26]	Network Lifetime Prolongation: Increased by 65.52%. Residual Energy Enhancement: Improved by 77.05%	• Achieves an increase in network lifetime.	Pizzza	• Complexity in cluster formation and maintenance. • Potential impacts on scalability and adaptability in dynamic environments.
Sarvesh Kumar Sharma1 and Mridul Chawla [27]	Prolonged network lifetime, with the first dead node reporting after 7000 rounds. Supported heterogeneity factors of 10%, 20%, and 40%.	• Enhances network lifetime. • Increases the number of alive nodes. • Reduces energy consumption by minimizing CH selection frequency.	PRESEP	• Complexity in implementing the hybrid approach. • Requires calibration to maintain optimal performance across diverse network conditions.
M. Thurai pandian et al. [28]	The proposed method achieves a 91.8% probability of a node becoming a cluster head, with a success rate of 97.8%, 0.22%	Enhances scalability and performance in large-scale RFID networks.	Fuzzy Logic in RFID Networks	• Complexity in Fuzzy Logic implementation. • Challenges in communication and energy management as

	accuracy, and 2.64% error rate. It effectively supports up to 1,000 nodes with 13 cluster heads, resulting in a latency of 36.91 seconds.			the network scales.
Puneet Kaur et al. [29]	It demonstrates lower energy consumption and higher cluster head consistency compared to existing protocols, achieving a better packet delivery rate	• Reduces energy consumption in WSN for forest applications. • Extends the coverage lifetime of sensor nodes. • Utilizes a composite weighted metric for effective cluster formation and node scheduling.	EEWBP	• Increased complexity in implementation. • Requires accurate measurement of weighted metrics for optimal performance.
Nilabar Nisha U et al. [30]	It demonstrates an increase in network lifetime and performance, achieving the highest values in simulation results with a lifetime of 95.88 for 200 nodes, and maintaining above 91.8 for 1000 nodes.	• Improved energy efficiency and reduced data transmission collisions.	SBLDAR	• Complexity of multi-channel implementation. • Dependence on accurate trust assessments.

4 Analysis and discussion

This section evaluates models for optimal node localization techniques by analyzing key performance metrics, the methodologies used, and relevant publications. The performance metrics are essential for quantifying the effectiveness of each model, offering a clear benchmark for comparison. Additionally, the review of publications provides valuable context on the methodologies employed, highlighting the various approaches taken within the field.This comprehensive evaluation highlights both the effectiveness of the models and the diversity of strategies present in the literature.

A. Evaluation of methods: Figure 3 illustrates that the gray wolf algorithm is the most frequently utilized method in optimal node localization techniques, underscoring its increasing prominence in this area. Additionally, Table 2 provides a comprehensive overview of the various methods employed in this field, highlighting the different approaches for achieving optimal node localization.

Table 2: Analysis concerning methods

Methods	Reviewed papers
HMSFO-EARS	[1]
Improved gray wolf algorithm	[2][3]
MHCRT-EEWSN	[4]
Enhanced LEACH Protocol	[5]
IGWONL-UWSN	[6]
CLA	[7]
HCEDV-Hop	[8]
S11 and IEEE 802.15.6 CM3A path loss model	[9]
DAAG	[10]
HUWST	[11]

DECR	[12]
HEESR	[13]
MDC-IR-DV-Hop	[14]
TESEES	[15]
SVR+KF algorithm	[16]
DMCAP	[17]
NBEER	[18]
GF-EERP	[19]
EERBCR Protocol	[20]
Energy-Efficient Protection Model	[21]
GLCHS	[22]
PISAE with CORP	[23]
EEHCT	[24]
MLRP and H-TEEN	[25]
Pizzza	[26]
PRESEP	[27]
RFID Networks	[28]
EEWBP	[29]
SBLDAR	[30]

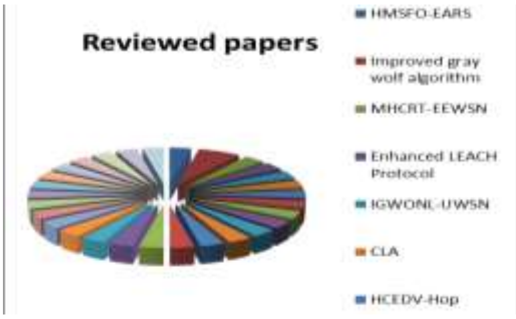

Figure 3: Analysis concerning methods

B. Evaluation of Metrics Achievements:

Figure 4 emphasizes that the key metrics frequently used in optimal node localization techniques include energy consumption, throughput, and network lifetime. These metrics are critical for assessing the overall performance and efficiency of various localization methods. Additionally, Table 3 provides an in-depth analysis of the results associated with these metrics, offering valuable insights into the effectiveness, strengths, and comparative benefits of different localization approaches.

Table 3: Analysis concerning metrics

Metrics	Reviewed papers
Energy Consumption	[1][4][5][7][12][13][14][16][17][18][20][22][26][27][30]
Delay	[1][17][19]
Throughput	[1][3][4][5][13][14][17][19][20][22][23][24][28][30]
Network Lifetime	[1][3][4][5][12][15][18][20][21][22][23][24][25][26][27][29][30]
Coverage Rate	[2]
Packet Delivery Ratio	[3][4][5][12][18]
End-to-End Delay	[4][5][12][18][23][30]
Packet Loss Rate	[4][10][20][23]

Number of Localized Nodes	[6]
Localization Error	[6][16]
no of alive nodes	[3][7][22][27]
no of packets	[3][7]
Localization Accuracy	[8]
Signal-to-Noise Ratio	[9]
Received Signal Strength Indicator (RSSI)	[9]
Bit Error Rate (BER)	[9]
RMSE	[10]
Energy Efficiency	[10][11]
Control Overhead	[12]
Cluster Building Time	[12]
Percentage of Security	[13]
latency time	[14]
traffic load reduction	[15]
RMSE	[16]
Data Delivery Ratio	[19]
Node Power Consumption	[21]
Number of Dead Nodes	[22]
Packet Forwarding Ratio	[22][23]
Energy Usage	[15][23]
Residual Energy	[26][29]
Accuracy	[28]
Success Rate	[28]
Error Rate	[28]
Stability	[14][24]

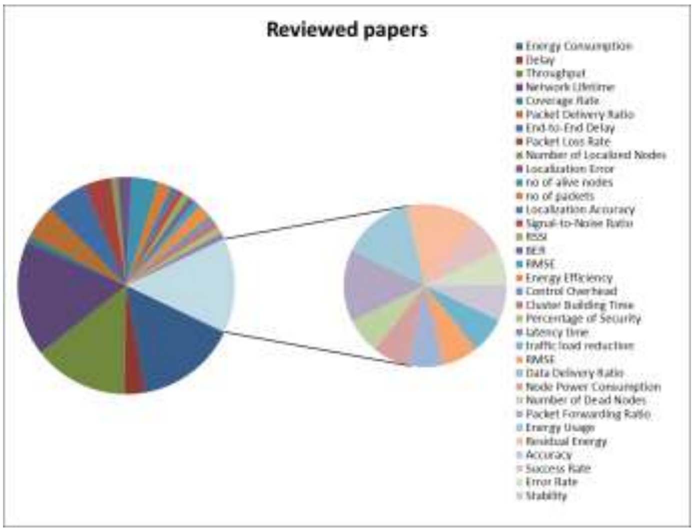

Figure 4: Analysis concerning metrics

C. Analysis based on year of publication

This section provides an analysis of the publication timeline for the reviewed journals, spanning from 2021 to 2024, as shown in Table 4. A key observation is the marked increase in publications related to optimal node localization techniques in 2023, indicating a surge in interest and notable advancements within that year. Further insights are offered in Figure 5, which visually represents the distribution of publications over time, highlighting the growing research activity and the accelerating momentum in this area.

Table 4: Analysis concerning year of publication

Publications	Reviewed papers
2021	[7]
2022	[4]
2023	[1][3][5][8][9][11][12][13][15][16][17][18][20][24][25][26][27][29][30]
2024	[2][6][10][14][19][21][22][23][28]

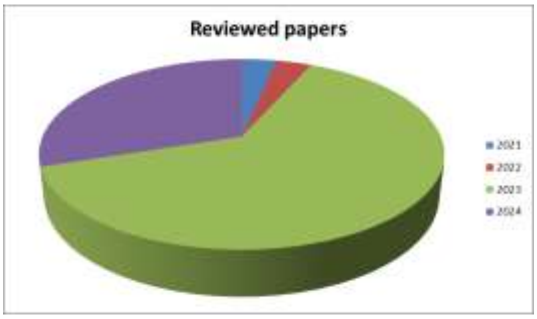

Figure 5: Analysis concerning year of publication

5. Research gaps and future works:

This section identifies critical research gaps in the field of optimal node localization for energy-efficient data transmission in IoT-enabled WSNs. These gaps highlight the limitations of current localization models and outline future research directions necessary for enhancing the effectiveness of localization techniques.

- Many existing localization techniques struggle to efficiently scale with an increasing number of nodes. For instance, Distance-based Localization Methods often face performance degradation as network size increases, resulting in reduced localization accuracy [4].
- Current models typically operate under controlled conditions and may not effectively adapt to dynamic environmental factors, such as mobility and interference. This lack of adaptability can lead to significant localization errors in real-world applications [6].
- Advanced localization algorithms, particularly those employing deep learning or complex optimization techniques, often demand substantial computational resources. This makes them challenging to deploy in resource-constrained environments typical of many IoT applications [8].
- Many existing algorithms do not meet the requirements for real-time localization due to delays in processing, particularly in techniques like Kalman Filtering. This limitation can hinder their applicability in time-sensitive scenarios [9].
- Current localization methods are often designed as standalone solutions and may not integrate well with other technologies or systems. This lack of interoperability can limit their use in diverse IoT environments [15].
- The effectiveness of localization models heavily relies on high-quality, accurate data. However, the availability of such data can be limited, especially in rural or less-developed areas, leading to performance issues in real-world deployments [16].
- Current models generally do not consider individual node characteristics or specific application requirements, which can affect the accuracy of localization. Personalized approaches may enhance performance by accounting for unique environmental and operational factors [18].
- Existing models may not adequately capture the variability in how different nodes operate under various conditions. This variability can lead to inconsistent performance, which is detrimental to system reliability [19].
- There is frequently a lack of consensus regarding the most effective metrics for evaluating localization performance, which results in inconsistent comparisons across studies and impedes the establishment of standardized best practices in the field [10].

5.1 Future Works for Optimal Node Localization in IoT-assisted WSNs:

To address the identified research gaps, future work should consider the following directions:

- Research should focus on developing adaptive localization algorithms that can learn and adjust to dynamic environmental conditions. This could involve incorporating machine learning techniques to improve accuracy and responsiveness to changes in the operating environment.

- Future models should focus on enhancing energy efficiency by incorporating low-power techniques, such as LEACH, to minimize node energy consumption while maintaining localization accuracy.
- Investigating optimization methods to improve the speed and efficiency of localization algorithms, such as Simultaneous Localization and Mapping (SLAM), can enhance their real-time capabilities.
- Exploring the integration of advanced technologies, such as edge computing and 5G networks, into localization techniques could significantly enhance performance and efficiency.
- Establishing standardized metrics for evaluating localization algorithms will enhance comparability across studies and facilitate the development of more effective techniques.
- Developing models that take into account individual characteristics and requirements can lead to improved accuracy and reliability in diverse deployment scenarios.
- Carrying out extensive field trials to validate the performance of localization techniques in real-world scenarios is essential for ensuring their practical applicability and reliability across various environments.
- Future research should explore collaborative localization techniques, where multiple nodes assist each other, to enhance overall accuracy and energy efficiency.

By addressing these gaps and focusing on future research directions, the field of optimal node localization can evolve, leading to more effective and reliable data transmission in IoT-assisted WSN.

6. Conclusion:

In conclusion, this survey underscores the significance of optimal node localization for energy-efficient data transmission in IoT-enabled WSNs, emphasizing its critical role as a key research area. While substantial progress has been made in developing localization techniques, persistent challenges such as scalability, adaptability to environmental changes, and computational efficiency continue to hinder implementation. Through a comprehensive review of a wide array of relevant studies, this research highlights both the strengths and limitations of current localization approaches, including clustering, routing, hybrid methods, and the integration of machine learning models. The insights derived from this analysis provide a deeper understanding of existing methodologies while pinpointing key areas for improvement, such as optimizing real-time performance and incorporating emerging technologies to further advance the field. Ultimately, this study seeks to guide future advancements in localization strategies, promoting more reliable and energy-efficient data transmission across various IoT applications, and contributing to improved system performance and sustainability.

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