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A Systematic Review of Metaheuristic Approaches to the Deployment Problem in Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) are widely applied in various fields, such as healthcare, security, agriculture, and education, where they simplify complex tasks and enable advanced monitoring. However, effective deployment remains a critical challenge in WSNs, affecting coverage, connectivity, energy efficiency, and network lifespan. Despite the importance of deployment optimization, no comprehensive Systematic Literature Review (SLR) has been conducted on metaheuristic approaches to address this challenge. This paper systematically reviews the demographic distribution, state-of-the-art metaheuristic solutions, and experimental evaluation methods related to the WSN deployment problem. A total of 112 studies were analyzed to address key research questions. Our findings provide a structured overview of current methodologies and identify significant research gaps. Key challenges observed include limited availability of open datasets, over-reliance on simulation validation, and the lack of comprehensive performance metrics such as latency and delay. These insights suggest future research directions for further optimizing WSN deployment.

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I. INTRODUCTION

Wireless Sensor Networks (WSNs) consist of small, cost-effective sensor nodes designed to monitor and control physical and environmental parameters such as sound, vibration, light, temperature, pressure, and movement [1]. These sensor nodes either process data locally or transmit information to external networks for advanced analysis [2]. The versatility of WSNs has revolutionized sectors such as healthcare, security, agriculture, and education by enabling advanced monitoring and control, solving previously insurmountable challenges [3].

Despite this transformative potential, WSNs face a critical obstacle known as the deployment problem (DP), which significantly impacts coverage, connectivity, energy efficiency, and network lifespan [4]. The DP arises from the need to maximize sensing coverage, maintain optimal network connectivity, and minimize energy consumption, often with a limited number of sensors [5]. Addressing these competing demands requires sophisticated optimization strategies that balance resource consumption with performance.

Metaheuristic algorithms have emerged as powerful tools for addressing the DP, providing near-optimal solutions to complex optimization challenges where traditional methods fall short [6]. While numerous studies have proposed metaheuristic-based solutions for the DP in WSNs, a comprehensive evaluation of recent advancements and validation methodologies remains lacking, leaving a critical gap in the research landscape [7].

This systematic literature review (SLR) bridges this gap by analyzing advancements in metaheuristic approaches for the WSNs deployment problem between 2015 and 2024. The study rigorously evaluates validation techniques, identifies key research gaps, and provides insights into demographic trends, research intensity, and performance metrics. These contributions form a robust foundation for advancing WSN deployment optimization and addressing unresolved challenges in the field.

The primary contributions of this study are as follows:

- A systematic review of the DP in WSNs based on metaheuristic approaches.
- A comprehensive analysis and synthesis of existing research in this domain.

- Identification of current research challenges and future directions for researchers.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 describes the methodology. Section 4 presents the findings, Section 5 discusses validity threats, and Section 6 concludes the study.

II. RELATED WORK

This section reviews existing surveys on the Deployment Problem (DP) in Wireless Sensor Networks (SNs) using metaheuristics, identifying research gaps addressed by this study.

The study in [8] surveyed metaheuristics for the DP in WSNs, covering WSN fundamentals, DP challenges, and a comparative analysis of various metaheuristic approaches. While it provided a foundation, it lacked coverage of recent methods and demographic insights. Similarly, [9] analyzed WSN deployment techniques and classified coverage strategies into force-based, grid-based, metaheuristic-based, and computational geometry-based approaches. This study evaluated performance metrics and compared WSN simulators but did not explore validation processes or challenges specific to metaheuristic methods in depth.

The study in [10] followed Systematic Literature Review (SLR) guidelines to survey WSN deployment strategies, categorizing mechanisms as deterministic or nondeterministic. However, it lacked detailed methodological analysis and quality assessment (QA). Likewise, [11] reviewed WSN deployment techniques, classifying coverage strategies into metaheuristic-based, classical, and self-scheduling approaches. Although it analyzed each category's strengths and weaknesses, it did not focus on recent advancements or demographic distribution in metaheuristic solutions.

Several other reviews have explored metaheuristic optimization in WSNs. The review in [12] examined algorithms and challenges in WSM optimization from 2010 to 2020. Similarly, [13] presented a systematic mapping study on optimization algorithms for sensor deployment in smart city applications, while [14] analyzed AI-based methods and proposed a comprehensive optimization model with constraints for WSN deployment. These studies evaluated algorithms such as genetic algorithms, particle swarm optimization, and ant colony optimization through simulations but lacked a dedicated focus on the DP and recent advancements in metaheuristic applications. Additionally, [15] explored trends in coverage, deployment, and localization using AI in WSNs, highlighting swarm intelligence, evolutionary computation, and fuzzy logic for deployment optimization. However, it did not provide detailed insights into the DP in WSNs, including rigorous study selection and QA. While these surveys provide valuable insights into WSN deployment techniques, they lack a systematic review of research intensity, DP solutions in WSNs, standardized QA, detailed validation methods, and comprehensive performance metrics for existing proposals.

This study addresses these research gaps by presenting a systematic review of metaheuristic approaches to the DP in WSNs, analyzing 112 selected studies. The key contributions of this study are as follows:

1) Analysis of publication trends and research intensity,
2) Synthesis of metaheuristic solutions to the DP
3) Evaluation of validation methods and performance measures across the selected studies,
4) Identification of research challenges and future directions.

By addressing these gaps this study provides valuable insights that lay a strong foundation for optimizing the WSN DP using metaheuristics.

Table 1
Related Work

Ref	Publication Analysis	DP	Validation	Metrics	Challenges	SLR
[8]	X	✓	✓	X	✓	X
[9]	✓	✓	X	✓	X	X
[10]	X	✓	✓	X	X	✓
[11]	X	✓	X	X	✓	X
[12]	✓	X	X	X	✓	X
[13]	X	✓	X	✓	✓	✓
[14]	X	X	X	X	✓	X
[15]	X	✓	X	X	✓	X
This Work	✓	✓	✓	✓	✓	✓

III. REVIEW PROCESS

This section outlines the process for conducting our SLR. Following [16], this study identifies and interprets research evidence, applying inclusion and exclusion criteria to define its scope. The SLR approach is used to identify research gaps in the DP in WSNs and analyze existing metaheuristic solutions in relation to our Research Questions (RQs).

A. Research Questions (RQs)

The SLR is conducted based on the following RQs:

- RQ1: What is the publication intensity in the research field?
- RQ2: What recent solutions have been explored for solving DP in WSNs?
- RQ3: What validation methods are used to evaluate existing proposals?
- RQ4: What performance measures are employed by the selected studies?

B. Search Process

The search process utilized five prominent databases: ACM, Web of Science, Scopus, Dimensions, and IEEE Xplore, focusing on journal articles and conference proceedings. To ensure comprehensive coverage, a systematic manual search was conducted to extract relevant studies. Although SpringerLink was excluded due to access constraints, its omission had minimal impact for several reasons. First, the selected databases collectively provide extensive coverage of high-quality publications in WSNs and significantly overlap with SpringerLink’s content. Second, forward and backward snowballing techniques were employed to identify pivotal studies that may not have been retrieved through database searches. Finally, prior research indicates that SpringerLink provides limited unique content beyond what is available in Scopus and Web of Science, particularly in engineering and technology-focused disciplines.

C. Search terms

Formulating precise search terms is essential for identifying relevant studies in this SLR [17]. The search terms, derived from the research questions, cover key aspects of the research problem. Keywords were applied across electronic databases to gather data, using synonyms and interchangeable terms for comprehensive coverage. Additionally, Boolean operations were used to refine and enhance search efficiency. The keywords used in the search included: "Deployment Problem," "WSN," "metaheuristic," "Wireless Sensor Network," and "Issues."

D. Inclusion and Exclusion Criteria

This section describes the study selection process and criteria for article inclusion. A total of 112 key papers were selected. Providing insights into the DP in WSNs using metaheuristics. Table 2 presents the inclusion and exclusion criteria.

Table 2
Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
The paper focuses on the DP in WSNs using metaheuristics.	Duplicates studies.
The paper has the potential to answer at least one RQ.	Papers outside the scope of this study
The paper is published in the English language.	Papers that are not peer-reviewed, have no full text, or fail to address at least one RQ.
The paper is available for download.	Papers written in non-English languages.
Papers published from 2015-2014	Papers published outside 2015-2024

E. Study Selection Procedure

The study selection process identifies relevant primary studies that directly address the research questions. It was conducted in multiple stages to minimize bias and ensure consensus, as shown in Figure 1. Initially, duplicate articles were removed from the 1,128 collected studies. Next, studies were excluded based on titles and abstracts, followed by a full-text review, reducing the number to 304 articles screened. To enhance coverage accuracy, snowballing techniques were applied to the 337 studies, examining forward citations and analyzing references for backward citations. Articles not meeting the inclusion criteria were excluded, resulting in a final selection of 112 publications for this research.

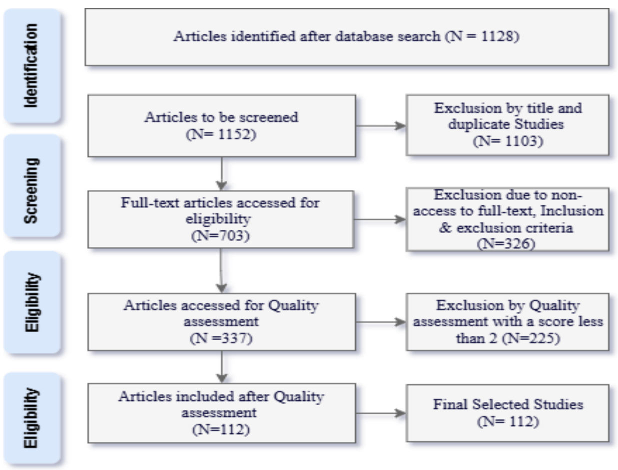

Figure 1. Study Selection

F. Quality Assessment (QA)

QA is a vital step in the SLR, designed to ensure the credibility and relevance of the selected primary studies [18]. This study implemented a comprehensive QA process, drawing on a survey format informed by prior systematic reviews[19, 20]. To maintain rigor and consistency, a four-point QA scoring system was employed. QA scores were assigned based on clearly defined criteria, as shown in Table 3, ensuring an objective evaluation of each study's quality.

Table 3
QA Questions

Question	Possible Answers
Does the paper outline proposals for the DP in WSNs?	Yes = 1, Partially = 0.5, No = 0
Does the paper state validation method?	Yes = 1, Partially = 0.5, No = 0
The paper describes the performance metrics?	Yes = 1, Partially = 0.5, No = 0
The paper contribution was clearly stated?	Yes = 1, No = 0

G. Data Extractions

At this stage, the authors thoroughly reviewed the full texts of the selected studies, storing key information in a structured Microsoft Excel file. The final list of papers provided data to address the research questions, capturing details such as: paper title, reference ID, publication year, type, and responses to research questions 1 through 4. Not all papers addressed every research question, but the extracted data ensured comprehensive coverage of the study's objectives.

IV. RESULTS AND ANALYSIS

This section presents the results for each RQ defined in section 3A.

A. RQ1: What is the publication intensity in the research fields

This RQ provides a detailed publication analysis of the 112 selected studies. To address it, the analysis is organized into four sub-sections: Publication Channel and QA Score, Publication Source, Publication Trends, and Citation Impact.

1. Publication Channel and Quality Score

As shown in Figure 2, three primary publication channels were identified: Journals, Conferences, and Symposiums. Journals accounted for 61% of the selected studies, followed by Conferences at 38%, and Symposiums at just 1% (2 studies). This distribution underscores the dominance of journals as the preferred publication venue, indicating a high standard for research quality. However, it also highlights untapped potential for high-quality publications in alternative venues such as workshops, magazines, and symposiums. The QA evaluation of the selected studies, based on criteria detailed in Section III-F, revealed that most studies are of high quality. Appendix results show that 72% of studies achieved a perfect QA score of 4, 27% scored between 3 and 3.5, and only one study (S29) scored below 3. This high quality is likely attributed to the prominence of journals and leading conferences as publication venues.

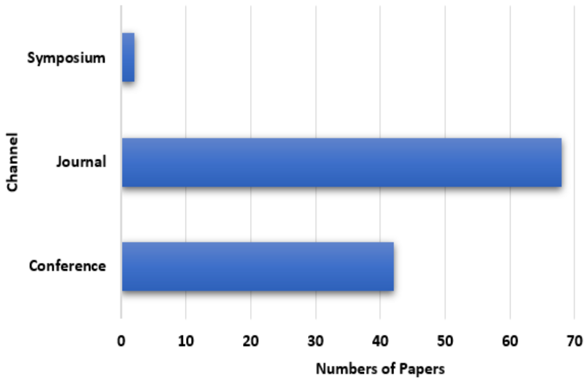

Figure 2. Publication channels

2. Publication Source

Table 4 summarizes the selected studies by publication sources, highlighting those with the most research contributions in the field over the past decade. The table also lists the publishers of these studies, A total of 71 publication sources were identified, with each conference paper originating from a unique publication. Notably, the journals IEEE Access (S47, S50, S51, S64, S76) and Wireless Personal Communications (S46, S52, S62, S67, S84) contributed five studies each, all achieving a high QA score of 3.5 or above, as detailed in the QA section of the Appendix.

Table 4
Publication Source

Publication Venue	Identifier
IEEE Access	S47, S50, S51, S64, S76
Wireless Personal Communications	S46, S52,S62, S67, S84
Wireless Networks	S68, S82, S71, S89
Journal of Ambient Intelligence and Humanized Computing	S72, S79, S80, S83
Applied Intelligence,	S53, S97
Applied Sciences	S103, S104
Wireless Communications and Mobile Computing	S98, S99
Information Sciences	S55, S73
Applied Soft Computing,	S58, S81
Sustainability	S87, S88
Computer Systems Science and Engineering	S90, S91
Intelligent Automation & Soft Computing	S92, S93
European Conference on the Applications of Evolutionary Computation	S1
International Conference on Ubiquitous Computing and Ambient Intelligence	S2
International Conference on Ad-Hoc Networks and Wireless	S3
International Conference on Broadband and Wireless Computing, Communication and Applications	S4
Proceedings of the Second International Conference on Computer and Communication Technologies	S5
Advanced Engineering Optimization Through Intelligent Techniques	S6
International Conference on Computational Intelligence, Communications, and Business Analytics	S7
Advances in Decision Sciences, Image Processing, Security and Computer Vision	S8
National Radio Science Conference (NRSC)	S9
International Electrical Engineering Congress (iEECON)	S10
International Conference on Information Systems and Technologies	S11
National Systems Conference (NSC)	S13
IEEE SENSORS	S12
International Conference on Computing and Network Communications (CoCoNet)	S14
International Conference on Communication Software and Networks (ICCSN)	S15
International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT)	S16
International Wireless Communications & Mobile Computing Conference (IWCMC)	S17
International Conference on Inventive Systems and Control (ICISC)	S18
International Conference for Convergence in Technology (I2CT)	S19
Joint International Information Technology and Artificial Intelligence Conference (ITAIC)	S20
International Conference on Electrical, Electronics, Engineering Trends, Communication, Optimization And Scie..nces (Eeecos 2016)	S21
International Symposium on Wireless Systems within the International Conferences on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS-SWS)	S22
International Conference on Control, Automation and Robotics (ICCAR)	S23
International Symposium on Networks, Computers and Communications (ISNCC)	S24
International Conference on Smart Structures and Systems (ICSSS)	S25
International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)	S26
International Conference on Computing, Communication and Networking Technologies (ICCCNT)	S27
International Conference on Networking and Network Applications (NaNA)	S28
International Conference on Electronics, Computers and Artificial Intelligence (ECAI)	S29
International Conference on Computer Systems, Electronics and Control (ICCSEC)	S30
Wireless days	S31
International Conference on Data Science and Communication (IconDSC)	S32
International Conference on Intelligent Control and Information Processing (ICICIP)	S33
International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS)	S34
Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)	S35
IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications	S36
IEEE Trustcom/BigDataSE/ISPA	S37
Chinese Automation Congress (CAC)	S38
International Conference on Parallel and Distributed Systems (ICPADS)	S39
International Conference on Digital Information and Communication Technology and its Applications (DICTAP)	S40
Signal Processing and Communications Applications Conference (SIU)	S41
Intelligent Biomedical Data Analysis and Processing	S42
IEEE Sensors Journal	S43
Arabian Journal for Science and Engineering	S44
International Journal of Wireless Information	S45
IEEE Transactions on Industrial Informatics	S48
Procedia Computer Science	S49
Computers & Electrical Engineering	S54
Journal of Network and Computer	S56
MDPI Proceedings Journals	S57
Soft Computing	S59
Security and privacy	S60
ISA transactions	S61
IEEE Communications	S63
Symmetry	S65
IEEE Transactions on Mobile Computing	S66
Mobile Networks and Applications	S69
International journal of communication system	S70
Computer Networks	S74
Advances in Manufacturing	S75
Chinese Journal of Electronics	S77
Intelligent Automation & Soft Computing	S78
Telecommunications and Radio Engineering	S85

Neural Computing and Applications	S86
International Journal for Traffic and Transport Engineering	S94
Sensor Review	S95
Mathematical Statistician and Engineering Applications	S96
International Conference on Cloud Computing, Data Science & Engineering	S100
International Conference on Inventive Computation Technologies	S101
International Journal of Informatics and Communication Technology	S102
Inteligencia Artificial	S105
Energies	S106
Entropy	S107
Evolutionary Intelligence	S108
Solid State Technology	S109
KSII Transactions on Internet & Information Systems	S110
Journal of Scientific & Industrial Research	S111
International Journal of Computer Networks and Applications	S112

3. *Publication Trend*

Figure 3 shows the total number of studies published from 2015 to 2024, highlighting key trends in research activity. In 2015, only 10 studies were published, marking the lowest activity in this period. A steady increase followed, peaking in 2019 with 18 publications, reflecting a growing focus on the DP in WSNs using metaheuristics. After 2019, research activity declined sharply, with publications dropping to 15 in 2020, 10 in 2021, and 7 in 2022. This decline aligns with the COVID-19 pandemic's impact, which likely disrupted funding, collaboration, and fieldwork. By 2023, activity rebounded to 11 studies, suggesting that researchers adapted to post-pandemic conditions. However, the drop to just 2 studies in 2024 indicates a possible shift in research priorities toward emerging technologies or newer domains.

The trends highlight three periods of decline (2019–2020, 2020–2021, and 2023–2024) and two growth phases (2018–2019 and 2022–2023). While research in this area has fluctuated, recent activity suggests a waning interest. Future studies could explore how global events, and evolving priorities have shaped these patterns.

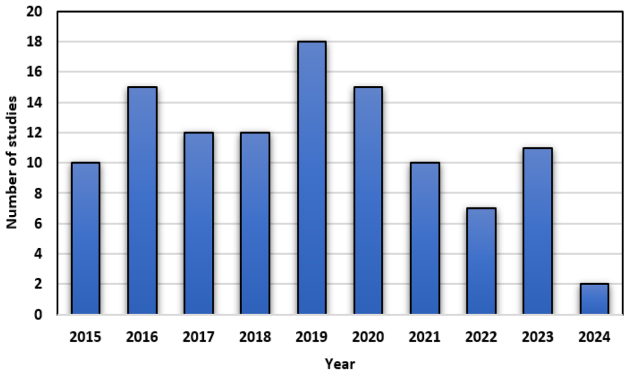

Figure 3. Publication Trends

4. *Citation Impact*

This study reveals that citation counts are influenced by factors such as publication source and date, with older papers generally accumulating more citations, as depicted in Figure 4. Journal articles were found to have higher citation counts than conference papers, reflecting the greater influence of journals in this research domain. Citation data, sourced from Google Scholar, indicates that this area is impactful but still emerging. Given the study's timeframe (2015–2024) and the field's novelty, only five journal articles (S43, S44, S52, S54, S56) exceeded 50 citations, while no conference papers reached this threshold. Citation counts may vary over time due to evolving research dynamics.

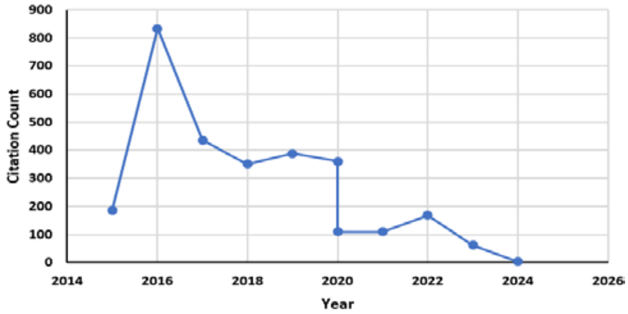

Figure 4. Citation counts

B. *RQ2: What are the recent solutions exploited for solving the DP in WSNs?*

This study identifies numerous solutions for addressing the DP in WSNs. Lanza et al. introduced two multi-objective genetic algorithms, NSGA-II and SPEA2, configured through a parametric sweep to optimize three conflicting objectives: average coverage, average energy cost, and average reliability in WSNs [21]. The results indicated that SPEA2 achieved the best performance. In another study, Kumar and Ranga utilized swarm intelligence to determine optimal relay node locations in polynomial time [22]. Their approach aims to populate the relay node system (RNS) to restore damaged areas and re-establish connections. Simulation results demonstrated improved performance compared to state-of-the-art solutions. Mnasri et al. proposed a hybrid algorithm named AcNSGA-III, integrating NSGA-III and Ant Colony Optimization (ACO) to address the challenge of deploying 3D nodes in WSNs [23]. This algorithm outperformed traditional NSGA-III and ACO.

Similarly, Ozera et al. developed a simulation system based on a genetic algorithm for actor node placement in Wireless Sensor and Actor Networks (WSANs) to enhance effective sensing and acting in WSNs [24]. This system generates problem scenarios with diverse distributions of programs, sensors, and actors. Additionally, Banka and Jana proposed a PSO-based algorithm, PSO-MSPA, for multi-sink placement in WSNs [25]. This algorithm was developed using an improved particle molecular scheme and new functions, yielding superior results compared to existing algorithms. In the study by Rao et al., a three-dimensional WSN was developed to tackle the point coverage issue at a minimal cost [26]. The results showed a 25% improvement in network performance, attributed to balanced energy utilization for optimal sensor nodes placement. The study by Singh et al. proposed a Quantum-Inspired Genetic Algorithm (QIGA) for relay node placement in cluster-based WSNs, aiming to minimize the number of nodes while ensuring connectivity between them [27]. The results indicated that this algorithm outperformed existing methods. Syed et al. developed a solution using the Ant Lion Optimization (ALO) algorithm to enhance the coverage rates in sensor networks, effectively addressing the coverage problem in WSNs [28]. The findings revealed that ALO outperformed other algorithms in convergence speed, performance, and objective value. Abo-Zahhad et al. proposed a centralized deployment algorithm based on an immune optimization technique to enhance the coverage of mobile sensor networks [29]. This algorithm enables high-speed sensors to optimize coverage based on detection types, with simulation results showing better performance than the CSAPO algorithm in coverage area, energy consumption, and convergence speed.

Additionally, Aziz et al. introduced a pure gravitational search algorithm (PureGSA), a variant of the gravitational search algorithm, aimed at maximizing WSN coverage using a binary sensing model [30]. Results indicated that PureGSA outperformed GSA, achieving better coverage. The study of Baidar et al., proposed a Whale Optimization Algorithm (WOA) to solve the problem of node location [31]. The proposed algorithm computes node locations based on several steps to analyze the entire network area. The simulation results showed good performance in terms of localization error and computing time. Balaji et al. developed a Particle Swarm Optimization (PSO) algorithm to address the Q-coverage problem, optimizing sensor positions to meet Q-coverage constraints [32]. This PSO method identified optimal positions for Q-coverage, outperforming random deployment. De et al. conducted a comparative analysis of three established deployment algorithms: grid-based self-deployment and optimization techniques using Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) [33]. Results indicated that the grid method was particularly effective for sensor deployment when sensors were randomly distributed in the central region of the area of interest. Additionally, Deif and Gadallah evaluated the performance of four existing algorithms for the Mobile Clustered Coverage Deployment Problem (MCCDP) using stochastic optimization techniques [34]. The experimental results revealed that the Greedy Heuristic (GH) performed the worst, while both the Ant Colony Optimization (ACO) and the Fuzzy Logic Genetic Algorithm (FLGA) excelled.

In another study, Fan proposed a method for arranging nodes in a designated zone using an intelligent algorithm. This method predicts potential traffic and energy consumption and designs a deployment model [35]. Simulation studies showed that this method reduces complexity and overhead within the lower value. Additionally, George and Sharma proposed a modified genetic algorithm for relay node placement in WSNs, aiming to minimize relay nodes while maximizing connectivity between sensor and relay nodes [36]. Experimental results demonstrated the algorithm’s effectiveness. Hajjej et al. proposed the Multi-Objective Flower Pollination Algorithm (MOFPA) for sensor node placement, focusing on balancing multiple objectives [37]. MOFPA outperformed NSGA and PSO in performance tests. Hasson and Finjan developed a deployment technique to enhance coverage, connectivity, and reliability in WSNs by using the angle between sensor nodes and neighbors [38]. Results showed high coverage and strong connectivity.

Kittur and Jadhav compared heuristic and artificial bee colony (ABC) algorithms based on network lifetime, finding ABC more efficient and optimal for extended network life [39]. To maximise WSN coverage, Kong and Yu introduced an improved PSO algorithm, which produced better results in terms of coverage area growth [40]. Laturkar and Bhavani used a PSO-based algorithm (Grid-Based Particle Swarm Optimization) to analyze sensor deployment, showing that MDBPSO outperformed regular PSO in iteration efficiency and time efficiency [41]. Liu et al. proposed an Ant-Lion Optimization method for WSN node deployment to maximize network coverage, with experiments indicating successful optimization of node locations [42]. Metiaf and Wu modified PSO to consider obstacles, yielding improved fitness, service life, and sensor energy efficiency [43]. Results showed that the modified algorithm outperformed the benchmark in terms of fitness values, service life, and energy consumption. Mnasri et al. presented a genetic algorithm designed to maximize WSN coverage area and optimize audio localization [44]. The algorithm finds the best solution for the coverage problem. The results showed a significant improvement in quality performance over random deployment and existing methods. Ramkumar suggested a fruit fly algorithm to eliminate overlapping nodes, based on the probability of coverage, to maximize the network lifetime in different WSNs [45]. The algorithm effectively addressed optimization challenges, showing a higher reduction rate in both non-redundant and redundant nodes compared to existing schemes during node placement.

Additionally, Njoya et al. proposed an algorithm-based multi-objective approach to optimize sensor node positions while maximizing disjoint cover sets [46]. Implementing this algorithm requires designing an objective function. Results showed that this approach outperformed existing methods in the literature. Sapre and Mini determined the minimum relay nodes needed for fault tolerance and full connectivity using the mean shift algorithm alongside metaheuristic methods like MFO, DE, Bat, and BBO[47]. Simulation results showed that the MFO algorithm outperformed other approaches. Shieh et al. proposed an improved algorithm to solve the node location problem and reduce the location error in WSNs, thereby enhancing the number of target nodes localization [48]. Simulation results showed no changes in execution time efficiency. Singh et al. analyzed coverage and various optimization algorithms used in WSN deployment, classifying coverage techniques based on geographical structures [49]. Their review indicated that computational geometry is the most widely used and efficient deployment technique. Similarly, Song and Qu used the standard Particle Swarm (PSO) algorithm to address WSN coverage issues, investigating how particle flight speed affects convergence by adjusting the speed limit [50]. Results showed a continuous increase in coverage rate during the iterative process. Tisseli et al. developed a novel heuristic to determine the minimum number and optimal placement of relay nodes (RNs) to repair disconnected networks with a grid topology in WSNs [51]. The algorithm ensures connectivity through Steinerized edges, and the results showed that the proposed heuristic outperformed the hybrid approach.

Likewise, Umashankar et al. proposed an algorithm to reposition nodes, reducing overlap while improving connectivity and coverage in a wireless communication network [52]. The proposed algorithm has a lower time cost compared to the genetic algorithm and offers maximum coverage with minimal time cost. Liping et al. presented an optimal sensor deployment method for target detection and location, formulating a sensor delivery model and introducing an objective function with two constraints for the optimization problem [53]. Simulation results showed that the solution performed better in solving the sensor DP. Wang et al. proposed a method for designing an efficient and optimized WSN for dairy farming addressing poor coverage and connectivity issues in traditional WSNs [54]. Their algorithm identified the best nodes to optimize the network. Simulations showed that the PSO algorithm quickly and efficiently optimized the overall WSN layout, overcoming the influence of fixed sensor nodes, achieving rapid convergence, and improving effective coverage. Xiang et al. introduced a hybrid sensor network using the Cuckoo Search (CS) algorithm to improve coverage in static sensor nodes and reduce deployment costs associated with mobile sensor nodes [55]. The algorithm is simple, easy to implement, and has strong global optimization capability. Simulation experiments demonstrated its effectiveness. Yu et al. introduced a new algorithm to assist in node placement for a WSN that monitors underground tunnel infrastructure. The algorithm relies on information exchange through social interactions between particles. Simulation results indicated that the optimization algorithm performs well.

Zhao et al. proposed a new sensor deployment scheme based on the Fruit Fly Algorithm (FOA) to improve coverage in WSNs [56]. The fruit fly's superior sense of smell and vision allows it to quickly identify food sources, making it an effective model. Experimental results showed that the FOA-based sensor deployment achieved faster convergence and higher coverage rates. Zhou et al. developed a method for deploying sensors by optimizing the topology of WSNs using the NSGA2 algorithm [57]. This mature and efficient method addresses multi-objective problems. Simulation experiments demonstrated that the method provides a more reasonable topology and higher location accuracy for WSNs. Zorlu et al. proposed a GPU-based solution using parallel genetic algorithms to increase the coverage of a homogeneous WSN topology in a two-dimensional Euclidean region [58]. The algorithm iterates and searches for new solutions until termination, with results showing an increase in performance. Zorlu and Sahingoz developed a genetic algorithm aimed at improving coverage in WSN topology with homogeneous sensors in a 2-D Euclidean space [59]. The proposed algorithm was tested with various sensor nodes and sensitivity ranges, showing both effectiveness and efficiency. Additionally, Zorlu and Sahingoz introduced a genetic algorithm combined with local optimization for positioning sensor nodes in a two-dimensional area [60]. Experimental results demonstrated that the algorithm effectively achieved the desired coverage.

Abdel-Basset et al. proposed an enhanced metaheuristic, the Multi-Verse Optimizer with Overlapping Detection Phase (DMVO), to optimize WSN area coverage [61]. The algorithm was tested on a large dataset with various criteria, showing efficiency and consistency compared to other algorithms. Moh’d Alia and Al-Ajouri introduced a harmony search-based distribution algorithm to optimize sensor node quantity and placement, maximizing coverage while minimizing network cost [62]. The algorithm was adapted to automatically determine the optimal number and positions of sensor nodes, demonstrating efficiency and superiority. Arora and Singh proposed a node location scheme using the Butterfly Optimization Algorithm, a metaheuristic inspired by natural phenomena, to estimate sensor node positions in WSNs [63]. The algorithm utilizes sensory receptors to locate food/nectar sources, outperforming other methods in precision and computation time. Ayinde and Hashim proposed using the Gravity Search Algorithm (GSA) and Differential Evolution (DE) to optimize relay node positions, maximizing network lifetime [64]. This algorithm follows gravitational law, where objects attract each other proportionally to their mass and inversely to the square of the distance. Experimental results showed that DE outperformed ABC and GSA in deploying relay nodes in a 3D setup. Benatia et al. proposed the Multi-Objective Distribution Strategy (MODS) [65]. MODS applies multi-objective evolutionary algorithms to address the WSN distribution problem, with results highlighting its effectiveness.

Bouzid et al. developed a new method to optimize node placement, analyzing existing methods in the literature to identify their limitations[66]. This approach generates optimal deployment based on the required topology, environment, and application specifications. Simulation results demonstrated its feasibility and effectiveness. Cao et al. proposed novel distributed, parallel multi-objective evolutionary algorithms (MOEA) to implement WSNs in 3D smart cities heterogeneously [67]. Results demonstrated that the novel algorithm effectively addressed implementation challenges, optimizing both performance and uptime. Chakravarthi and Kumar applied a non-dominant genetic classification algorithm (NSGA-III) to optimize WSNs through meta-heuristics, finding NSGA-III to outperform multi-objective Pareto evolutionary approaches [68]. The comparison shows that the NSGA-III algorithm surpasses the multipurpose Pareto-based evolutionary approach. Deif and Gadallah proposed an ACO-based method to achieve reliable WSN coverage at minimal cost, with results confirming its effectiveness [69]. Du combined distributed particle swarm optimization (DPSO) with a 3D virtual force (VF) algorithm for better sensor distribution in 3D terrains, showing improved coverage and connectivity [70].

Goyal and Patterh introduced a bat-inspired metaheuristic, integrating bacterial foraging principles, which showed greater node localization accuracy and efficiency than its predecessors [71]. Gumaida and Luo developed a Hybrid PSO with Variable Neighborhood Search (HPSOVNS) that enhanced location accuracy despite RSSI errors [72]. Gupta et al. designed a genetic algorithm (GA) for minimal yet effective node placement to meet coverage and connectivity needs [73]. Hanh et al. proposed MIGA, an advanced GA for maximizing coverage in WSNs with varied detection ranges, demonstrating stability and solution quality [74]. Hashim et al. used an Artificial Bees Colony (ABC) approach to extend the WSN lifespan, with results showing network durability improvements [75]. Lanza-Gutiérrez et al. tackled multitasking RNPP problems in WSN using MO-FA, achieving robust performance across varied instances [76]. They further developed relay node energy harvesting methods optimizing cost, sensitivity, and reliability across varied scenarios [77]. For static WSNs, their MO-VNS approach significantly outperformed other algorithms in energy and sensitivity metrics [78]. Mihoubi et al. introduced Dopeffbat, a bat algorithm variant using Doppler effects for improved precision and convergence over standard PSO [79]. Mnasri et al. presented two PSO variants, including acMaPSO for diverse, optimized 3D IoT deployments, enhancing population diversity and avoiding local optima [80].

Mohtashami et al. proposed a multi-objective optimization (MOO)-based approach accommodated non-uniform event patterns, demonstrating strong performance in simulations [81]. Ng et al. introduced a Smart Bat Algorithm (SBA) incorporating decision theory and fuzzy logic for 3D WSN deployment, demonstrating superior robustness across deployment stages [82]. Qasim et al. developed an ACO-based algorithm to optimize 3D WSN deployment, reducing node costs [83], while Qiao et al. introduced the DSLC algorithm to avoid local optima, improving complex WSN deployment problems [84]. The method improves algorithm search, preventing local traps and enhancing accuracy in complex optimization problems. Saad et al. developed a Bresenham-based coverage model for 3D WSN DP using a multi-objective genetic algorithm [85]. Results demonstrated the effectiveness and efficiency of the proposed approach. Sapre and Mini introduced the Moth Flame Optimizer (MFO), Internal Search Algorithm (ISA), and Bat Algorithm (BA) to determine optimal relay node (RN) placement locations [86]. The simulation results showed that MFO requires fewer relay nodes than ISA, BA and M1tRNP approach, which is based on a minimal spanning tree. Sapre and Mini proposed a Moth Flame Optimization (MOMFO/D) algorithm based on multi-objective decomposition, which decomposes the objectives into several single objectives to solve the relay node placement problem [87]. The proposed algorithm outperformed the other approaches, as indicated by the results. Sayad et al. proposed a Chemical Reaction Optimization (CRO) algorithm, inspired by interactions between molecules in chemical reactions, to achieve a low stable energy state, to solve the problem of router node deployment (WMN-RNP) in wireless mesh networks (WMN) [88]. The algorithm simulates molecular interactions, achieving stability and improving client coverage and network connectivity.

Senouci et al. introduced an algorithm that optimizes a swarm of binary particles, incorporating a novel position update method for quicker convergence and utilizing the abandonment concept to mitigate premature convergence [89]. The proposed method integrates binary particle swarm optimization with WSN deployment needs to create an efficient, lightweight sensor placement algorithm, outperforming state-of-the-art methods. Shabir et al. developed an optimized Ant Colony Optimization (ACO) algorithm to identify disjoint sensor node subsets [90]. The ACO seeks for the optimal scheduling scheme among sensors to maximize the number of disjoint complete cover sets, demonstrating superior performance over earlier methods. The study of [91] developed a hybrid gravitational search algorithm combined with a social ski-driver model (GSA-SSD) to enhance coverage and connectivity in WSNs. This hybrid approach to target-based WSN optimizes coverage and connectivity requirements. The algorithm excels in sensor activation, open area speed, and network duration.

Tam et al.proposed two new methods to reduce the transmission loss of sensor nodes to extend the network lifespan under load-balancing constraints [92]. The algorithm utilizes a popular clustering method that groups a set of points into k clusters, each characterized by its centroid. Results showed that the proposed methods outperformed the existing methods. Tsai introduced a metaheuristic algorithm known as Search Economics (SE) for deploying WSNs [93]. SE's key feature is its capability to represent the solution space based on previously evaluated solutions and to leverage knowledge gained during the search process. Results indicate that SE outperformed other methods. Ling Wang et al. developed a multi-objective node deployment model aimed at enhancing reliability, real-time performance, cost efficiency, and scalability in industrial WSNs (IWSNs) [94]. They generated three large-scale node deployment scenarios as benchmarks to validate the proposed model and algorithm. Results showed that the proposed model was superior to the other four algorithms, making it suitable for large scale IWSN design with guaranteed reliability and efficient real-time performance. Wang et al.proposed two new flower pollination algorithms (IFPA and NSMOFPA) for WSNs heterogeneous nodes implementation, addressing obstacles in the monitoring area [95]. The algorithm employs cross-pollination for global optimization and self-pollination for local optimization, enhancing its convergence speed and optimization capabilities. Results showed that the NSMOFPA algorithm effectively optimizes WSN implementation, providing better solutions. Yang et al. proposed a novel sensor placement method, combining image processing and an AI algorithm, to optimize coverage on a 3D surface using a limited number of sensors [96]. Simulation results showed that the proposed method is remarkable and efficient.

Yu et al. studied the deployment of relay nodes in traditional WSNs, optimizing average energy consumption and network reliability [97]. The algorithm encodes its individual into chromosomes as part of the EA. Results showed that NSGA-II achieved the best performance across all instances. ZainEldin et al. introduced an improved dynamic implementation technique based on the genetic algorithm (IDDT-GA) to maximize the coverage of the area with the least number of nodes and minimize overlap area between neighboring nodes [98]. In the proposed algorithm, nodes are randomly deployed in the target area, demonstrating superior efficiency compared to other advanced techniques. Zameni et al. developed an efficient algorithm known as NDTCR (Node Deployment for Target Coverage in RWSNs), which identifies the quantity and placement of sensors through a two-phase process [99]. The algorithm minimizes the number of installed sensors while ensuring target coverage and connectivity, with results showing that NDTCR requires fewer sensors with an acceptable run time. The study in [100] introduced a new model and two metaheuristic algorithms-Genetic Algorithm and Particle Swarm Optimization- for coverage maximization in WSNs. This approach incorporates heuristic initialization, a novel fitness function, an improved virtual force algorithm, uniform deceleration in inertia weight calculations, and the impact of leading individuals in subpopulations. Results showed that these algorithms outperformed GA, ICS, and CFPA.

Kulkarni et al. introduced a Modified Shuffled Frog Leaping Algorithm (MSFLA) to achieve accurate sensor localization by treating area-based localization as a two-dimensional optimization challenge using biologically inspired metaheuristics [101]. Result showed that MSFLA-based localization achieved higher accuracy than other geometric trilateration methods. In another study, [102] proposed a hybrid meta-heuristic technique combining Artificial Bee Colony (ABC) and Differential Evolution (DE) algorithms to enhance energy efficiency and network lifetime through a novel clustering scheme and dynamic mobile sink placement strategy. The study by [103] presented a swarm-based dragonfly approach within their Meta-heuristic Optimized Opportunistic Routing Protocol, which optimizes forwarder node selection by considering residual energy and Euclidean distance. This method demonstrated enhancements in packet delivery ratio (PDR) and energy consumption over existing protocols. Meanwhile, [104] improved the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol by integrating the Grey Wolf Optimization (GWO) algorithm for more effective cluster head selection, resulting in notable gains in network lifetime and energy efficiency.

Similarly, [105] proposed the Mutant Grey Wolf Optimizer (MuGWO) algorithm, which demonstrated superior coverage and connectivity maintenance, particularly in high node density and complex environments. The study by [106] developed an Improved Metaheuristic-Driven Energy-Aware Cluster-Based Routing (IMD-EACBR) scheme that employs the Archimedes Optimization Algorithm and Teaching-Learning-Based Optimization to enhance clustering and routing, leading to higher network lifetime and energy efficiency. [107] addressed the issue of low coverage in WSNs using the Improved Marine Predator Algorithm (IMPA), which improved exploration and exploitation capabilities, leading to better coverage rates. [108] used the Whale Optimization Algorithm (WOA) for dynamic node deployment, optimizing convergence speed, network coverage, and energy consumption. The study of [109] introduced a Multi-Objective Firefly Algorithm (MOFA) for optimizing WSN layout design, achieving 100% area coverage and full connectivity with improved energy consumption.

Another study in [110] developed the Enhanced Metaheuristics with Trust-Aware Secure Route Selection Protocol (EMTA-SRSP), which focuses on secure route selection using an oppositional Aquila Optimization Algorithm, demonstrating superior performance across multiple network metrics compared to other methods. [111] integrated Type-II Fuzzy Logic with the Butterfly Optimization Algorithm for their TFL-BOARS technique, improving cluster head selection and route optimization, enhanced WSN performance and longevity. The study of [112] analyzed six meta-heuristic algorithms for sensor node deployment, concluding that the Whale Optimization Algorithm (WOA) was the most effective in energy utilization and network coverage. [113] employed Bee Colony Optimization (BCO) for optimizing traffic detector placement, demonstrating better CPU time efficiency and solution quality compared to Simulated Annealing (SA). The Cluster Head Selection in [114] achieved enhanced node survival and network longevity, while [115] used Rider and Sailfish Optimization for energy-efficient cluster head selection and routing in IoT networks. The BAT-SA algorithm proposed by [116] enhanced node localization accuracy in WSNs. [117] created the algorithm for Competitive Multi-Objective Marine Predators (CMOMPA), optimizing heterogeneous WSN deployment, achieving superior convergence and performance. [118] proposed an improved meta-heuristic approach for optimizing WSN coverage rates, demonstrating effectiveness in dense deployment scenarios. [119] employed the Differential Evolution technique in their Metaheuristic Load-Balancing-Based Clustering Technique (MLBCT), resulting in improved network lifetime and stability. [120] introduced the Whale Optimization Algorithm-based Clustering Technique (WOA-P), significantly improving network lifetime and throughput. [121] proposed Energy-Balanced Greywolf Optimization (EBGWO) for efficient clustering and routing in Software-Defined WSNs. [122] presented the Multi-Objective Firefly Algorithm-Based Relay Node Placement (MOFF-RNP) to optimize relay node deployment. [123] used Integer Linear Programming and Swarm Intelligence for efficient WSN deployment, achieving high coverage and minimal energy consumption.

In [124], an Enhanced Sparrow Search Algorithm (ISSA) for node localization was proposed, demonstrating smaller localization errors. [125] developed a hybrid algorithm called BAGOA that integrates the Bees Algorithm and Grasshopper Optimization Algorithm for optimal WSN deployment. Additionally, in [126] the Meta-heuristic-based Secure and Energy-efficient Routing (MHSEER) protocol for the Industrial Internet of Things (IIoT) was introduced, resulting in enhanced throughput and a lower packet drop ratio. Furthermore [127], combined the Gannet Optimization Algorithm and Differential Evolution in their Surrogate-Assisted Hybrid Meta-heuristic Algorithm (SAGD) for WSN coverage optimization. [128] used a many-objective optimization approach with the Decomposition-based Evolutionary Algorithm (θ-DEA) for WSN deployment, optimizing multiple conflicting objectives. [129] evaluated three multi-objective optimization algorithms for WSN deployment, finding MO-JPSO to generate more non-dominated solutions. Finally, in [130] a combination of Ant Colony Optimization and a fuzzy decision engine was applied for energy-efficient routing, resulting in notable reductions in energy consumption and latency. Meanwhile, in [131], the Grey Wolf Optimization (GWO) algorithm was utilized for routing in Marine Underwater Sensor Networks, leading to improved network longevity and operational efficiency.

C. RQ3: What validation methods are used to evaluate existing proposals?

To address this RQ, we analyzed the validation methods employed in the selected studies to assess their proposed solutions. The SLR identified five primary validation methods: Simulation, experiment, comparison, dataset, and statistical procedure. Simulation was the most prevalent method, used in 62 studies, highlighting its flexibility and effectiveness in modelling WSN scenarios and testing various configurations. Experiments, found in 27 studies, provided practical insights but were limited by real-world constraints. Comparisons, appearing in 14 studies, facilitated benchmarking against established approaches. Only two studies employed datasets, possibly due to the limited availability of standardized data in WSN research. Statistical procedures, used in a single study, suggest potential for more rigorous quantitative assessments in future work. Finally, six studies lacked validation methods, indicating a transparency gap. Figure 5 provides further details.

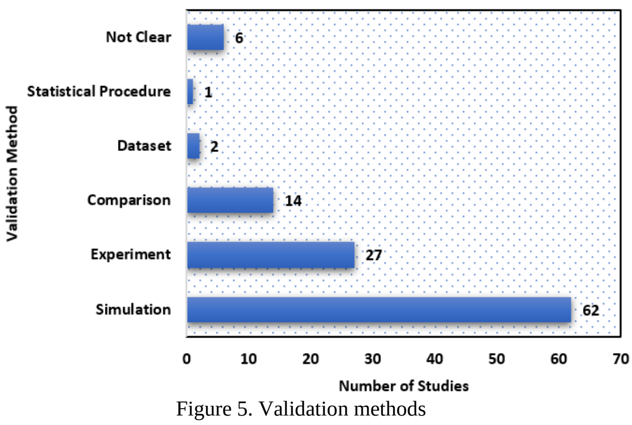

Figure 5. Validation methods

D. RQ4: What performance measures are employed by the selected studies?

The selected studies employed a range of performance measures, as detailed in the Appendix, with many utilizing multiple metrics. We identified ten distinct performance measures across these studies. The most common measures were: Performance was used in 46 studies (41%), Efficiency was adopted in 19 studies (17%), Network Coverage appeared in 18 studies (16%), Energy Consumption was included in 16 studies (14%) and Network Lifetime was considered in 14 studies (13%). The prevalence of performance as a primary measure reflects the focus on algorithm proposals, where performance evaluation is crucial. Overall, performance and efficiency remain significant concerns when addressing decision problems in WSNs. Table 5 presents the performance measures used in the selected studies.

V. DISCUSSION

This section is organized into two parts: the first presents the research findings, while the second outlines key challenges and suggests future research directions.

A. Research Findings

This study addressed four RQs and performed an SLR on DP in WSNs using metaheuristics. From 1,124 identified papers across five databases, 112 primary studies met the inclusion criteria. These studies revealed notable trends, including stable demographics over nine years and a research peak in 2016, with 489 citations. A decline from 2017 to 2020 followed, likely due to saturation after the 2015–2016 surge. Global factors, such as the COVID-19 pandemic, may have further disrupted research focus during 2020–2022, with studies dropping from 15 in 2020 to 7 in 2022. A renewed interest in 2023, with 11 studies, suggests recovery, but the sharp drop to 2 studies in 2024 highlights ongoing challenges. Further investigation is needed to clarify these trends and their underlying causes.

We identified the three most frequent publication venues: IEEE Access, the Journal of Ambient Intelligence and Humanized Computing, and Applied Soft Computing. QA analysis revealed that 72% of the selected studies received the highest score of 4, while 27% scored between 3 and 3.5, indicating high quality in both the studies and the research domain. Among the proposed solutions, algorithms were the most common, present in 60% of the studies, followed by approaches (23%) and models (6%). In response to RQ3, we found five validation techniques: Simulation (62 studies), Experiment (27 studies), Comparison (14 studies), Dataset (2 studies), and Statistical Techniques (1 study). Additionally, six studies did not clearly specify their validation methods. A variety of performance metrics were adopted to evaluate the effectiveness of the proposals addressing decision problems in WSNs. Among the 112 selected studies, only three studies [S4, S10, S60] did not clearly specify their performance measures. The most common and frequently used metrics were Performance (46 studies), Efficiency (19 studies), and Network Coverage (18 studies).

B. Challenges and Future Research Directions

This subsection highlights key research challenges identified in the SLR on DP in WSNs, requiring attention from both novice and experienced researchers. Although research activity in this domain has been substantial, recent focus in DP in WSNs has declined, underscoring the need for renewed investigation. Most validation methods rely predominantly on simulation (62 studies), followed by experiments (27) and comparisons (14 studies), while only two studies utilize datasets. This indicates a need for open dataset evaluations, which suggests the importance of developing and utilizing open datasets to improve the generalizability of proposed solutions. Additionally, some studies lack clarity in their proposals and validation methods, highlighting the need for more explicit descriptions. Furthermore, while performance, efficiency, and network coverage are commonly used metrics, future research should expand to include measures like latency, data transmission, and delay to enhance evaluation rigor.

Future researchers are encouraged to explore the integration of WSNs with the Internet of Things (IoT) and edge computing to unlock transformative possibilities in real-time data processing and scalability. Leveraging IoT protocols and standards can facilitate seamless communication between WSNs and IoT ecosystems, enabling innovative applications in domains such as smart cities, healthcare, and industrial automation. Additionally, deploying edge nodes within WSNs presents an opportunity to reduce latency by processing data closer to its source, thereby improving energy efficiency and enhancing network responsiveness. Finally, the design of metaheuristics tailored for dynamic and heterogeneous WSN environments remains a key challenge. Future studies should investigate adaptive metaheuristic frameworks capable of self-tuning in response to environmental changes, thereby improving robustness and performance.

VI. CONCLUSION

This study presents an SLR on the DP in WSNs using metaheuristics. From an initial 1125 papers, 112 were selected based on defined inclusion and exclusion criteria. The methodology ensured precise RQs aligned with the study's objectives, ensuring the inclusion of relevant studies. This research offers WSN researchers a detailed discussion on publication intensity, solutions utilized, validation methods, and performance measures for DP. Findings show that the selected studies comprise 44% conference papers, 44% journal articles, and 2% symposium papers, with no workshop or magazine papers. For QA, 72% of studies received the maximum QA score of 4, while 27% scored between 3 and 3.5. The main validation methods in the studies include simulation (most common, with 37 studies), experiment (23 studies), comparison, dataset, and statistical technique. A total of ten performance measures were identified, with the most common being performance (46 studies), efficiency (19 studies), network coverage (18 studies), energy consumption (16 studies), and network lifetime (14 studies). This SLR successfully meets its objective, answering all formulated RQs on DP in WSNs.

APPENDIX

Table 5
Performance Metric

ID	Ref	Performance Metric	QA Score
S1	[21]	Performance	4
S2	[22]	Performance	4
S3	[23]	Efficiency	4
S4	[24]	Not Clear	3
S5	[25]	Efficiency	4
S6	[26]	Energy consumption, network performance	4
S7	[27]	performance	4
S8	[28]	Network speed and performance	3.5

S9	[29]	Network coverage, Energy consumption and speed of convergence	4
S10	[30]	Not Clear	3
S11	[31]	Performance	3.5
S12	[32]	Network coverage, performance	4
S13	[33]	performance	3.5
S14	[34]	performance	3.5
S15	[35]	Energy consumption	4
S16	[36]	Effectiveness	4
S17	[37]	Performance	4
S18	[38]	Coverage, connectivity and reliability	3.5
S19	[39]	Network lifetime, efficiency	3
S20	[40]	WSN coverage, performance	4
S21	[41]	Performance	4
S22	[42]	Network coverage, Efficiency	4
S23	[43]	Energy consumption	3.5
S24	[44]	Network coverage, performance	4
S25	[45]	Network coverage, Network lifetime	3
S26	[46]	Efficiency	4
S27	[47]	Performance	4
S28	[48]	Accuracy and Efficiency	4
S29	[49]	Efficiency	2.5
S30	[50]	Network speed	3.5
S31	[51]	Performance	3.5
S32	[52]	Network Connectivity and Coverage	3.5
S33	[53]	Performance	4
S34	[54]	Network coverage	4
S35	[55]	effectiveness	4
S37	[56]	Efficiency and network coverage	4
S38	[57]	Accuracy	4
S39	[58]	Network coverage and performance	3.5
S40	[59]	Effectiveness and efficiency	4
S41	[60]	Effectiveness and network coverage	4
S42	[61]	Effectiveness, coherence and coverage	4
S43	[62]	Efficiency	4
S44	[63]	Performance	3.5
S45	[64]	Network Lifetime, efficiency	4
S46	[65]	Network Distribution	3.5
S47	[66]	Feasibility, performance and effectiveness	4
S48	[67]	Not Clear	3.5
S49	[68]	Performance	3.5
S50	[69]	Reliability and effectiveness	4
S51	[70]	Performance	4
S52	[71]	Speed	3.5
S53	[72]	Efficiency and accuracy	4
S54	[73]	Network coverage	4
S55	[74]	Network coverage, performance	4
S56	[75]	Durability	4
S57	[76]	Performance	3
S58	[77]	Performance	4
S59	[78]	Energy consumption, performance	4
S60	[79]	Not Clear	3
S61	[80]	Efficiency	4
S62	[81]	performance	4
S63	[82]	performance	4
S64	[83]	efficiency	4
S65	[84]	accuracy	4
S66	[85]	Effectiveness and efficiency	4
S67	[47]	Performance	4
S68	[87]	Performance	3.5
S69	[88]	Network connectivity and coverage	4
S70	[89]	Efficiency	4
S71	[90]	Performance	4
S72	[91]	Performance, network coverage and connectivity	4
S73	[92]	Network lifetime	4
S74	[93]	Performance	4
S75	[94]	Reliability, lifetime, costs and scalability	4
S76	[95]	Efficiency and reliability	4
S77	[96]	Coverage	4
S78	[97]	Energy consumption and network reliability	4
S79	[98]	Performance and efficiency	4
S80	[99]	Network coverage and connectivity	4
S81	[100]	Performance	4
S82	[101]	Accuracy	4
S83	[102]	Energy consumption, residual energy, and network lifetime	4
S84	[103]	Number of nodes, Throughput, Packet delivery ratio, and Energy Consumption	4
S85	[104]	Performance	4
S86	[105]	Performance	4
S87	[106]	Number of nodes, Network lifetime, Energy consumption, Packet delivery ratio (PDR), and Latency	3.5
S88	[107]	Performance	4
S89	[108]	Number of nodes, Network coverage, Energy consumption	4
S90	[109]	Network coverage, connectivity, lifetime, energy consumption and the number of nodes.	4
S91	[110]	Packet delay, Energy consumption, Latency, Throughput, Cluster overhead	3.5
S92	[111]	Performance	3.5
S93	[112]	Network coverage	4
S94	[113]	Performance	4
S95	[114]	Number node, Packet delivery, Network lifetime, Overhead	3.5
S96	[116]	Performance	4
S97	[117]	Inverted generational distance (IGD), hypervolume (HV)	4
S98	[118]	Network Coverage	4
S99	[119]	Network lifetime and network stability, Residual energy, and Packet delivery	3.5
S100	[120]	Network lifetime, stability period, Network energy, Throughput	3.5
S101	[121]	Network lifespan, residual energy, network throughput	4
S102	[122]	Number of nodes, Energy consumption and Network lifetime	3.5
S103	[123]	Network Lifetime, Coverage Ratio	4
S104	[124]	Performance	4
S105	[125]	Network coverage, overlapping area, average moving distance, and Energy consumption	4
S106	[126]	Throughput, Packet Drop Analysis, Delay Analysis, Energy Consumption, Faulty Routes Analysis	4
S107	[127]	Performance	3.5
S108	[128]	Performance	4
S109	[129]	Performance	4
S110	[130]	Performance	4
S112	[115]	Execution time, energy depletion, network delay, throughput, packet delivery, Number of nodes	3.5

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of the paper.

AUTHOR CONTRIBUTION

The authors confirm their contributions to this paper as follows: Study Conception and Design: Shamsu Abdullahi, Muhammad Garzali, and Abubakar Zakari initiated the research, supervised by Kamaluddeen Usman and Abdullahi Abubakar Imam. Data Collection: Conducted by Shamsu Abdullahi and Jaafar Zubairu Maitama. Analysis and Interpretation: Shamsu Abdullahi and Muhammad Garzali performed the analysis, with interpretation support from Abubakar Zakari. Manuscript Preparation: Drafting was led by Shamsu Abdullahi, with Kamaluddeen Usman, Abubakar Imam, and Abubakar Zakari reviewing and approving the final manuscript.

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