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RESEARCH ARTICLE

Localization and Deployment Considerations into Quality of Service Optimization for Energy-Efficient Wireless Sensor Networks

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Abstract – Wireless Sensor Networks (WSNs) have been more popular for a wide range of applications due to research ability to monitor and gather data from a variety of situations. However, it remains challenging to achieve Quality of Service (QoS) while maintaining energy efficiency. In the context of QoS optimization for energy-efficient WSNs, this study investigates the crucial issues of localization and deployment concerns. Localization the precise positions of sensor nodes are crucial for effective data fusion and routing algorithms that rely on localization. This study compares and contrasts several localization methods, including range-based and range-free approaches, and explains benefits and drawbacks. The study also investigates the effects on QoS and energy savings of various deployment strategies, including optimizing node location, boosting coverage, and increasing node density. The goal of this research is to find out how to optimize QoS in low-power wireless networks by including latency, throughput, and stability, among other quality of service characteristics, into the design of routing algorithms. Current routing protocols, like Low-Energy Adaptive Clustering Hierarchy (LEACH), are assessed for ability to optimize quality of service while minimizing energy consumption. In addition, this study explores several approaches that might help enhance QoS while reducing energy consumption, such as energy-aware routing, adaptive duty cycling, and data aggregation methods. By thoroughly examining and evaluating localization algorithms, deployment concerns, and routing protocols, this study offers practical and theoretical insights for researchers and practitioners aiming to optimize quality of service in energy-efficient WSNs. Useful and dependable WSN deployments in a wide variety of domains possible with the help of the presented results and suggestions.

Index Terms – LEACH, Node Density, Quality of Service, Range-Based Localization, Routing Protocols, Wireless Sensor Networks.

1. INTRODUCTION

Sensor nodes in a wireless sensor network communicate with one another using a wireless channel to carry out decentralized sensing operations. Miniaturized, inexpensive, and power-efficient sensor nodes make up its core, and it doesn't rely on any current infrastructure [1]. Every one of these nodes has four primary components a sensor unit, a processing unit, a transceiver, and a power unit that work together to collect data from immediate surroundings and transmit it to an external base station or sink. Properly configured nodes in a WSN can collaboratively execute signal processing activities to acquire information from distant and likely mission essential regions in an unsupervised and resilient manner, even when a single sensor node only has limited connection and compute capabilities [2]. The design of WSNs is among the most difficult in the field of wireless communication, despite its widespread use for applications such as environmental monitoring, target tracking, battlefield surveillance, industrial diagnostics, smart spaces, and security management. This is because sensor nodes communicate over long distances, using up a lot of limited energy resources when sending data to a sink [3].

The adaptability of WSN in data collection has contributed to meteoric rise in popularity. These networks have several important applications, including medical, agricultural, industrial, and environmental monitoring [4]. Must find methods to decrease energy consumption without compromising service quality, if want to make full advantage of WSNs. Achieving performance goals like low latency, high throughput, and dependable data transmission requires WSN-dependent applications to have excellent quality-of-service [5]. However, it is still not an easy job to achieve QoS without sacrificing energy efficiency. This study aims to optimize service quality for energy-efficient WSNs by addressing significant deployment and localization challenges [6]. Accurately determining the locations of sensor nodes requires the use of localization. The use of accurate location-based routing and data fusion are both significantly enhanced by it. This research compares range-based and non-range-based localization techniques. Taking into consideration the methods' impacts on service quality and energy efficiency, it weighs the benefits and negatives of each [7].

The Internet of Things (IoT) is a technical advancement that has sparked a new trend of physical goods learning new skills. Inspiring more and more of the material rely on every day to be digitally integrated; it is transforming the world around into an information ecosystem [8]. Through the interconnection of all things, are now able to get any kind of support at any time, from any location, and with any level of quality of service [9-11]. Interconnection of all physically visible items enabled by the internet on the embedded platform is the basis of this enabling technology [12, 13]. As an integral aspect of the Internet of Things, sensors are used in the process of data collection via sensing. Among the many components that make up the internet of things paradigm, wireless sensor networks stand out as a particularly promising system for gathering, processing, and disseminating data pertaining to the demands of the real world [14, 15].

One or more routers, access points, or a base station link the wireless sensor network to the internet of things, allowing for comprehensive monitoring of the internet-enabled linked network of things [16-18]. Due to the rechargeable nature of these wireless sensor networks, the routing mechanism used must be able to establish connections with low power consumption, long network lifetimes, and low latency and loss. Because of this, wireless sensor networks aren't always a good fit for traditional routing algorithms [19, 20]. Despite apparent efficiency, the current clustering-based routing techniques result in excessive energy consumption when dealing with the cluster head; hence, an improved routing approach that raises the bar for IoT-wireless sensor networks is required [21].

At the intersection of deployment and localization parameters lies the key to achieving optimal quality of service in the realm of WSNs while maintaining energy efficiency [22]. Despite WSNs' continual instrumentality in monitoring and capturing data across numerous settings, there is an ongoing difficulty with maintaining a balance between demands for quality of service and the vital need to conserve energy. This study delves into the essential components of localization techniques and deployment parameters [23-28] to optimize the quality of service for energy-efficient WSNs.

1.1. Motivation of the Paper

WSNs are becoming more widespread and employed in many applications, prompting this research. Monitoring and capturing data in various contexts make WSNs valuable in environmental monitoring, healthcare, smart cities, and industrial automation. WSNs must balance QoS with energy efficiency to operate efficiently. Quality of service is key for WSN applications. It covers dependability, latency, network longevity, and data validity, which affect network performance and efficacy. QoS metrics must be optimized in energy-constrained WSNs for dependable and efficient data collecting. Due to sensor nodes' limited power sources, WSNs must additionally prioritize energy efficiency. Network lifetime and energy utilization must be optimized to maintain network operation without battery replacement or recharge. This study addresses the challenge of maximizing WSN QoS and energy efficiency. This research focuses on localization and deployment to improve QoS and energy efficiency. It evaluates localization and deployment solutions for QoS improvement, highlighting pros and cons.

This paper is organized as follows. Section 2 of this paper provides an overview of localization techniques and applications with WSNs. Optimization of QoS is examined in relation to deployment concerns in Section 3. In Section 4, this research talks about how to include localization and deployment techniques into the overall QoS optimization framework. The trial outcomes and effectiveness assessments are presented in Section 5. The inquiry is wrapped up in Section 6, and suggestions for further study are provided.

2. LITERATURE SURVEY

Alghamdi, T. A. [2] By taking energy, latency, distance, and security into account, this research has introduced a new clustering model with optimum Cluster Head (CH). Various analyses have been conducted, including those on convergence, active nodes, normalized network energy, delays, risk probability, algorithms, and statistics. The results of the assessment demonstrated that the suggested model outperforms the alternatives. In comparison to the FireFly (FF), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), and DrAgon fly (DA) algorithms, the suggested model performed better in the 2000th round in active node analysis by 45.95%, 18.92%, 24.32%, and 24.32%, respectively.

Ben-Ghorbel, M. et al. [4] an efficient and cost-effective method for gathering data from WSNs utilizing a mobile Unmanned Aerial Vehicle (UAV) was outlined by the author. To reduce power consumption and maximize data collection from adjacent sensors, the proposed solution optimizes the UAV's flight path and data collection pauses. Optimal placement of UAV stops and sensor data acquired each stop were optimized by iterative use of a clustering-based technique and a Travel Salesman Problem (TSP) process, respectively, in the suggested algorithm.

Jaiswal, K., &Anand, V. [6] The multipath routing paradigm proved suitable for enhancing the quality of service in WSNs. Improved network performance and service quality are

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outcomes of the suggested protocol's use of an Optimality Factor (OF)-based routing strategy.

Kaur, A. et al. [7] Common criticisms of Distance-Vector (DV)-Hop and related weighted centroid DV Hop algorithms are high power consumption and lack of precision. Phase one of the Enhanced Weighted Centroid DV-Hop (EWCD) algorithms limits the broadcasting range by t hops, which increases localization accuracy and decreases power consumption. An average of the hop count, transmission radius, and average hop distance was used to generate the weight factor of the EWCD algorithm.

Ramesh, M. V. [11] One of the most effective ways to monitor disaster-prone regions in real-time was via wireless sensor networks. This research thoroughly examined the creation and implementation of a network of wireless sensors for landslip detection. The network can provide both real-time data via the Internet and advance warnings to the revolutionary three-tiered warning system that was designed for these author’s research. Methods for energy-efficient data collecting, fault-tolerant clustering algorithms and threshold-based data aggregation are all part of the system.

Singh, O et al. [17] these authors research proposes an Energy-Efficient Multipath Routing (EEMR) protocol for WSN with the aim of reducing the power consumption of the quality-of-service measures. A Lion multi-optimal optimization method was introduced to discover the best, energy-efficient path with the fewest nodes probable. The author built the suggested EEMR protocol in Matrix Laboratory (MATLAB) after comparing it to existing optimization approaches. Findings from the simulations show that the EEMR protocol achieves a high success rate with lower power consumption in WSN QoS-based routing.

Tuna, G., & Gungor, V. C. [19] underwater exploration and monitoring technologies were becoming more and more popular. Unfortunately, none of the implemented Underwater Acoustic Sensor Networks (UASN) applications were flawless because of the limitations and difficulties caused by the severe underwater environment. Many issues persist with the current state of underwater sensor network deployment. Understanding and examining the current advances in underwater acoustic communication and UASNs was crucial for effective implementation of various application scenarios and reaping advantages, notwithstanding the significant amount of research work focused on UASNs in recent years. Thus, UASNs need close collaboration between researchers and those responsible for implementing.

Muthurajkumar, S. et al. [22] these authors research proposes a novel secure routing method for Mobile Ad hoc Networks (MANETs) that uses trust score assessment to efficiently identify and avoid malicious nodes; the technique was termed Cluster and Energy Efficient Secure Routing Algorithm (CEESRA). It also proposes a novel method for evaluating trust scores and computing trust values in this study. In this study, a dynamic clustering approach was used to generate an energy-efficient safe routing algorithm. This technique takes into account low-mobility nodes, as well as trust levels, energy consumption, and distance characteristics. The results of the tests, which were carried out using Network simulator (NS) 2 simulations, show that the suggested algorithm outperforms the current methods in relation to residual energy, packet drop ratio, security, and throughput.

Kevin P, Samarakoon UT [27] these authors research provides a brief overview of some popular algorithms that use 3D static networks. The paper's algorithms are mostly based on very precise and accurate principles. These authors found that there are four possible topologies for a localization network: mobile anchor and static nodes, mobile anchor and static sensors, mobile anchor and both mobile and static, and mobile and static anchor-based. Based on factors such as localization accuracy, localization coverage, localization time, landmark number, and energy consumption, these authors have compiled a list of mobile node and landmark localization techniques.

N. Kumar et al. [29] the proposed Enhanced Energy-Efficient Clustering Approach-Tier Heterogeneous Wireless Sensor Networks (EEECA-THWSN) represents a novel and inventive solution to the challenges faced by Tier Heterogeneous Wireless Sensor Networks (THWSNs), where energy efficiency is paramount. The three-tier node structure, along with carefully selected parameters for CH assignment, demonstrates a holistic approach to prolonging network lifetime and reducing energy consumption.

Z. Yao [30-32] these authors research suggested and evaluated the performance of Hybrid Load Balancer (HLB), a load-aware Layer-4 Load Balancer (LB). Based on passively acquired networking observations abstracted from the data plane, HLB can predict both server occupancies and processing speeds, which are mentioned in this study as two essential criteria in load balancing performances. The comparison for existing works with advantages and limitations are represented at table 1.

2.1. Problem Definition

This study discusses energy-efficient WSN-QoS optimization. WSNs are widely used for data monitoring and gathering, although QoS and energy efficiency are challenging to achieve. This study focuses on localization and deployment. Localization is necessary for WSN sensor node positioning. Location-based data fusion and routing methods are efficient with accurate localization. Deployment techniques affect WSN energy efficiency and service quality. This research examines how node density, location optimization, and coverage improvement affect energy efficiency. To optimize

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QoS in energy-efficient WSNs, the study examines routing protocol design with QoS characteristics as dependability, latency, and network lifespan. QoS optimization and energy efficiency tradeoffs of LEACH, *SelEctive Polling* (SEP), and Sensor Protocols for Information via Negotiation (SPIN) routing protocols are examined.

Table 1 Comparison Table for Existing Work

Author	Year	Methodology	Advantage	Limitation
Alghamdi, T. A. [2]	2020	WSN	The hybrid dragonfly-firefly clustering model with optimum cluster head selection incorporates energy, latency, distance, and security, its key benefit.	Due to the computational difficulty of balancing energy, latency, distance, and security, the hybrid dragonfly-firefly method Cannot choose optimal cluster heads.
Ben-Ghorbel, M. et al. [4]	2019	Traveling Salesman Problem	The proposed energy-efficient UAV-based system intelligently picks stops to optimize wireless sensor network data collection and save energy.	For robust real-world performance, adaptability to dynamic environmental changes and probable effectiveness effects from unplanned occurrences are essential.
Jaiswal, K., &Anand, V. [6]	2019	Energy-Efficient Optimal Multi-Path Routing Protocol	This routing strategy optimizes wireless sensor network-based IoT performance by considering durability, dependability, and traffic intensity, minimizing unfairness under heavy traffic loads.	Sensitivity to dynamic network conditions can impact performance, necessitating adaptability measures for robustness.
Kaur, A. et al. [7]	2017	Weighted centroid algorithm	Proposed weighted centroid DV-Hop improves accuracy and reduces power consumption, overcoming traditional DV-Hop limitations in wireless sensor networks.	Sensitivity to factors and dynamic conditions can impact adaptability in diverse wireless sensor network scenarios.
Ramesh, M. V. [11]	2014	Heterogeneous wireless networks	Over three years, the wireless sensor network in landslide-prone regions collects data on rainfall, moisture, and geological characteristics, improving real-time catastrophe prevention.	Wireless sensor networks can monitor landslides, although maintenance, scalability, and adaption to disaster situations can need more research for long-term performance.
Singh, O. et al. [17]	2021	energy-efficient multipath routing	The Energy-Efficient Multipath Routing protocol for Wireless Sensor Networks uses the multi-objective lion optimization algorithm to optimize paths with lower energy consumption, outperforming state-of-the-art protocols in delay, throughput, and energy efficiency.	The complexity of the multi-objective lion optimization method can impair real-time speed and practical implementation of the Energy-Efficient Multipath Routing protocol, which is effective. Investigation and validation in many contexts are required.

Tuna, G., & Gungor, V. C. [19].	2017	underwater acoustic sensor networks	The proliferation of Underwater Acoustic Sensor Networks (UASNs) is driven by wireless sensor network advancements, leading to specialized deployment techniques and localization algorithms for diverse applications.	One limitation of Underwater Acoustic Sensor Networks (UASNs) is the challenge of signal propagation in underwater environments, leading to limited communication range and increased latency.
Muthurajkumar, S. et al. [22]	2017	Energy-efficient routing algorithm	Minimizes energy consumption in routing	Limited scalability in large-scale networks
Kevin P, Samarakoon UT [27]	2019	received signal strength indicator	This study reviews contemporary WSN localization innovations, including 3D and mobile anchor-based algorithms for environmental monitoring and disaster relief and performance analysis to increase static 3D localization accuracy.	The study examines WSN localization, although it can struggle to generalize approaches across applications and situations. Environmental conditions and system limits must be considered for effective implementation.
N. Kumar et al. [29]	2022	Enhanced energy-efficient clustering approach	The Enhanced EEECA for HWSN uses a three-tier node structure to pick cluster heads based on beginning energy, node condition, and residual energy.	Although promising, the proposed EEECA for HWSN can face scalability and adaptability issues in dynamic network conditions, requiring.
Z. Yao. [30]	2022	cloud and distributed computing	The HLB infers server statuses without explicit monitoring, improving response times and resource use over existing methods.	Although beneficial, the suggested HLB can struggle in varied and dynamic network contexts, requiring more research for maximum performance.

3. MATERIALS AND METHODS

The successful implementation of a comprehensive strategy for QoS optimization in energy-efficient WSNs hinges on a meticulous and well-considered approach to materials and methods.

3.1. Location of the Sensor Nodes

Accurate and effective sensing by a network relies on strategically placing sensor nodes. Quality of service and energy efficiency are two of many aspects that should be considered when deciding where to put sensor nodes.

Raising the transmission power of a network has a significant impact on its overall energy efficiency due to the increased energy consumption that follows.

Sensors in an environmental monitoring network, for instance, could have to be placed close to bodies of water, points of interest geographically, or pollution sources. The sensing system is made more effective by positioning the nodes in such a way that the network can collect data that is both accurate and representative. The sensor nodes in WSN architecture have been represented at figure 1.

In addition, network topology is critical for both energy efficiency and quality of service. Network topologies like star topology, cluster-based topology, or a hybrid mix of the two might be used depending on the particular application. To get the most out of the network, make sure that the sensor nodes are positioned according to the selected topology and the localization algorithm has been represented at algorithm 1.

Input:

- Network area: The geographical area to be covered by the sensor network.
- Phenomena of interest: Specific locations or factors that require accurate sensing.
- Energy constraints: Limitations on the energy consumption of the sensor nodes.

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- Network topology: The chosen topology for the sensor network.

Steps:

Setup:

Sensor Nodes (Unknown Locations): $P_i = (x_i, y_i)$ for $i = 1,2, \dots, n$.

Anchor Nodes (Known Locations): $A_j = (a_j, b_j)$ for $j = 1,2, \dots, m$

1. Distance Measurements:

Measure the distances between each sensor node and multiple anchor nodes. Let d_{ij} be the distance between the i^{th} sensor node and the j^{th} anchor node.

2. Trilateration Equations:

- The basic trilateration equation for a sensor node P_i is:

$$(x_i - a_j)^2 + (y_i - b_j)^2 = d_{ij}^2$$

- For m anchor nodes, you will have mm equations for each sensor node.

3. Solving the System of Equations:

- Formulate the system of equations using the trilateration equations for all sensor nodes.
- Use numerical methods or linear algebra techniques to solve the system and obtain the coordinates (x_i, y_i) for each sensor node.

Output:

Placement coordinates: The optimal coordinates for placing the sensor nodes.

Algorithm 1 Localization

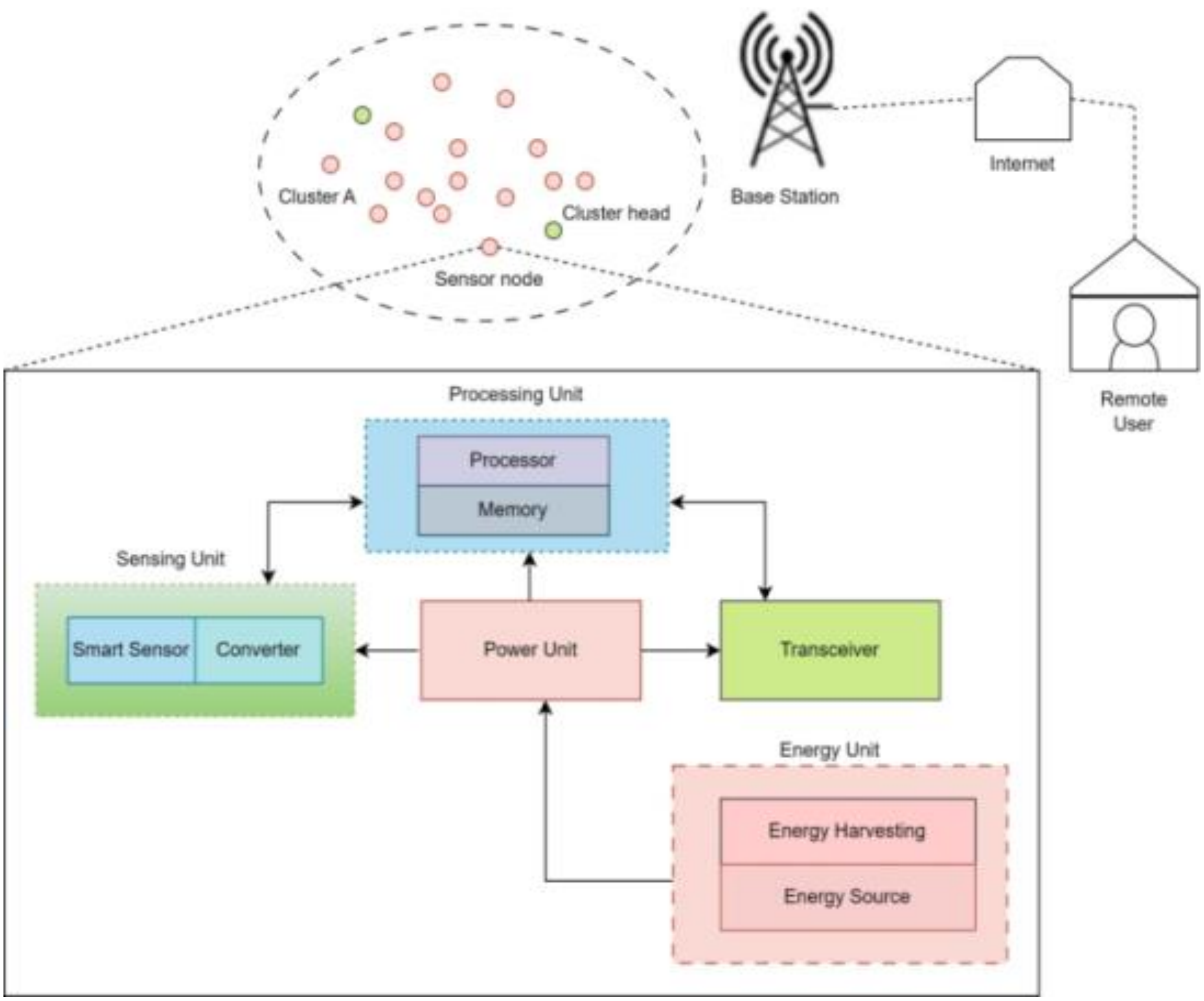

Figure 1 Sensor Nodes in WSN Architecture

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3.2. Particle Swarm Optimization

Plan the locations of the sensor nodes. Method for optimization with a swarm of very small particles. Particle Swarm Optimization (PSO) is an algorithm that mimics the cooperative strategies of natural communities, such as swarms of bees or schools of fish. Individuals in this method's population are called particles, and the swarm as a whole is called a swarm. These hordes stand for potential answers. The objective function's search space is started with random positions for the particles. After the initiation phase, the swarm's particles will settle on a location that strikes a balance between best past positionspbest, the best collective position (gbest), and a random search. Vectors V and X, reflecting the particle's current and past velocities in the search space and in relation to its paired particles, respectively, are used to represent each particle in PSO. Mathematical updates to particle locations and velocities are performed in line with Eqs. (1) and (2):

$$V_{id}(t+1) = w * v_{id}(t) + c_1 * r_1 * \left(pid(t) - x_{id}(t)\right) + c_2 * r_2 * \left(p_{gd}(t) - x_{id}(t)\right) \quad \text{------ (1)}$$

$$X_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad \text{------ (2)}$$

Where the particle's velocities at iterations t and t-1 are represented by $v_{id}(t)$ and v_{id} respectively the value of pi represents the ideal position of a particle. When compared to its contiguous neighbors at time t, p_{gd} is in first place. Each particle is pushed inexorably toward the pbest and gbest locations by stochastic acceleration factors, the strengths of which are represented by the coefficients c_1 and c_2 of acceleration. Two random numbers, r_1 and r_2, are shown below, both drawn from a uniform distribution between 0 and 1. When weighing global against local search, inertia weight x is used. If x_{id} is the particle's location at iteration$t$, then a high inertia weight promotes global exploration while a small one favors local exploitation. The first step of PSO is the random generation of particles in the search space.

3.2.1. Multi-Vector Particle Swarm Optimization

To improve PSO's insufficient exploration and exploitation potential, this research suggests as Multi Vector Particle Swarm Optimization (MVPSO). By increasing PSO's exploration, exploitation, and converge capabilities, MVPSO has made it possible to address the aforementioned problems with the original PSO method. Particle position vectors are updated at each iteration of the optimization process to the proposed mathematical equations that are incorporated to the PSO algorithm. The MVPSO algorithm has been represented at algorithm 2.

Each optimal solution in MVPSO is represented by a particle. The whole swarm of particles moves around the search space until it finds the best possible answer. MVPSO suggests adding three extra vectors for each particle in a D-dimensional hyperspace, where n is the population size. For each d [(1, d)], let $x_i = (xi_1, xi_2, \dots, xi_d)$ and let $v_i = (vi_1, vi_2, \dots, vi_d)$ denote the position and velocity, respectively. Equations (3-5) describe MVPSO's three position vectors as$(X_{1t}+1)_i$. Each particle's starting velocity and location are determined by random vectors within respective ranges. The location is modified using three equations.

Following are some equations used to update the particle's location in all three dimensions:

$$(X_{1t}+1)_i = (1+\alpha) * pbest - \alpha * pos \quad \text{---------- (3)}$$

In equation 4 for each iteration, the optimal solution in dimension i is represented by the coordinates [pbest], where $[X_{1t}]$.

$$(X_{2t}+1)_i = r * X_{1t} + 1 - (1-r) * pbest \quad \text{------- (4)}$$

In equation 5Where alpha is a constant equal to 0.2, pbest is the location of the optimal solution on iteration i, and $(X_{2t}+1)_i$ is the position on the second vector indicating the solution as of iterationi.

$$(X_{3t}+1)_i = \beta * pos - (1-\beta) * pbest \quad \text{---------- (5)}$$

Where alpha is a constant equal to 0.2, pbest is the i^{th} position of the best solution, and $(X_{3t}+1)_i$is the i^{th} position of the third vector in the current solution.

The aforementioned equations reveal that MVPSO relies on three distinct position vectors: X_1, X_2, and X_3. Each particle's X_1, X_2, and X_3 vectors indicate a different direction of motion it located anywhere along the path between the problem and the answer, or even beyond that range.

The approach is known MVPSO, after the three vectors used to create new coordinates surrounding each particle. Individuals' actions in the search space define particles. There are two principles that guide the search process:

1. The memory of each particle permits it to remember the better place it has previously passed.

2. Each particle will grow to a higher-quality location inside the three position vectors that surround it.

Particles update positions by adding own value to the best position value in the vector of nearest neighbor. Moreover, the position vector solutions to Equations (3), (4), and (5) are shown. As can be seen in the picture, the proposed equations create three new solutions to the search space, labeled P_1, P_2, and P_3. Although a two-dimensional model has been shown, this equation generalized to higher dimensions.

Solutions placed around one another using the locations provided by above equations. This ensures both discovery and use of resources in the region between the updated particle vector positions.

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MVPSO generates and analyzes new position vectors to see how compare to the particle. Particle motion and the distribution of the swarm's other particles are both affected by these newly produced locations. This indicates that the MVPSO approach thoroughly explores the area between the lower and upper boundaries of the search space. MVPSO has improved its search capabilities by include more particle locations throughout the particle movement, allowing it to find the global optimum while avoiding the problem of local minima.

Finding the promising parts of the search space and eventually settling on the global optimum requires an algorithm that can go through the search space without ever encountering a value that is beyond the search space's upper limit or lower limit.

Are adaptively modified to maintain exploration and exploitation within the search space:

$(X_{1t}+1)_i = \left((X_{1t}+1)_i * \left(\sim(\text{flub}+\text{flag41b})\right)\right) + \text{ub} * \text{Flaub} + 1\text{b}.* \text{F1a1b}$ --------- (6)

$(X_{2t}+1)_i = ((X_{2t}+1)_i.* \left(\sim(\text{F1aub2}+\text{f1a1b2})\right) + \text{ub}.* \text{Flaub2} + 1\text{b}.\text{F1a1b2}$ ------- (7)

$(X_{3t}+1)_i = ((X_{3t}+1)_i.* \left(\sim(\text{F1aub3}+\text{F1a1b3})\right) + \text{ub}.* \text{F1aub3} + 1\text{b}.* \text{F1a1b3}$ ------ (8)

Where $(X_{1t}+1)_i$ the position of the beginning vector is specified by Eq 6 The second location of the vector is $(X_{2t}+1)_i$ which is calculated using Eq. (7). Eq. (8) and the values of Flaub, Flaub2, and Flaub3 within the search space's upper and lower boundaries define the location of the third vector, $(X_{3t}+1)_i$.

Input:

- Population size (n)
- Dimensionality of the search space (D)
- Maximum number of iterations (max_iter)
- Lower bound (lb) and upper bound (ub) for each dimension

Algorithm Overview:

1. One should first seed the search space with a population of particles whose locations and velocities are completely random.

$$(X_{3t}+1)_i = \beta * \text{pos} - (1-\beta) * \text{pbest}$$

2. Second, use the objective function to determine how healthy each particle is.
3. Initialize the pbest (personal best) positions of each particle as current positions and the gbest (global best) position as the best position among all particles in the swarm.

$$(X_{2t}+1)_i = r * X_{1t} + 1 - (1-r) * \text{pbest}$$

4. For each iteration (t) up to the maximum number of iterations:

a. Update the three position vectors (X1, X2, and X3) of each particle based on the equations (3), (4), and (5) provided.

$$(X_{1t}+1)_i = \left((X_{1t}+1)_i * \left(\sim(\text{flub}+\text{flag41b})\right)\right) + \text{ub} * \text{Flaub} + 1\text{b}.* \text{F1a1b}$$

c. Update the particle velocities and positions using equations (1) and (2) provided, considering the pbest and gbest positions.

Output:

Optimal solution found by the algorithm.

Algorithm 2 MVPSO

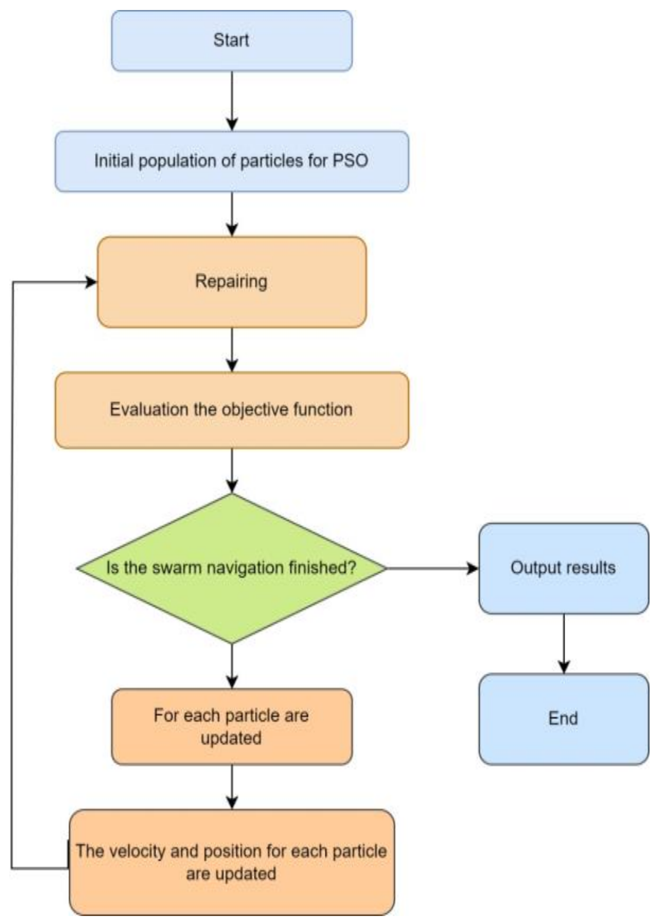

Figure 2 MVPSO Architecture

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Each particle's location and speed define its trajectory across the search region. Each particle's fitness is calculated using the problem's objective function. The method then sets each particle's pbest position to its present location and the gbest position to the particle's position relative to the rest of the swarm. After this initialization phase, the main iteration loop starts, and at each iteration, the algorithm modifies the position vectors of each particle using the equations from previous iterations (equations 6, 7, and 8). Particles' methods of searching and capitalizing on the best places identified so far are outlined by these equations. The MVPSO algorithm has been represented at figure 2.

3.3. Received Signal Strength Indication

The path-loss prediction process begins when reference samples have been gathered. To begin, N points will be used for making forecasts. The closest reference point is then determined for each forecast point. Path-loss estimated using reference data such as the distance between a reference location and an A wireless sensor point or the Received Signal Strength Indicator (RSSI). This equation estimates the path-loss at each given forecast pointn:

$$\mathrm{PL_n[dB]} = \mathrm{p_{0_k}} - 10\mathrm{n}\log_{10}\left(\frac{\mathrm{d_{p_n}}}{\mathrm{d_{o_k}}}\right) \text{------ (9)}$$

In equation 9 the circles representing predictions are white, whereas the circles representing references are dark. The closest reference point is indicated by the number under the prediction point in the set of numbers shown before the circle.

The suggested technique has the potential benefit of allowing the user to choose own number of prediction points. Despite being able to fill as many prediction points as feasible, this research employs the same amount of the prediction samples to provide a level playing field with current systems. The new model drastically saves the time spent collecting samples by cutting down on the number of samples needed. Path-loss at the reference point is highly correlated with path-losses at the prediction spots since the two are physically near to one another.

Wireless Fidelity signal attenuation is very variable and susceptible to interference in the densely packed display hall of a science and technology museum. The acquisition terminal's signal strength is not constant, even when it is collecting data from the same A wireless sensor point from the same location. That is to say, the range of possible variations in signal intensity is quite narrow. In order to mitigate the impact of random fluctuations on the final computed result, this research employs a technique that averages the results of many acquisitions and measurements. However, in practice, even if many a wireless sensor points are gathered from the same location, fluctuations will have distinct amplitude changes. The RSSI algorithm has been represented at algorithm 3.

Input:

- Reference samples: a set of N reference points with associated path-loss values and corresponding coordinates $(\mathrm{d_{pn}}, \mathrm{PL_n})$ for n = 1 to N.
- Forecast points: a set of M forecast points with corresponding coordinates $\mathrm{d_{ok}}$ for k = 1 to M.

Algorithm Overview:

1. Initialize an empty list to store the predicted path-loss values for each forecast point: $\mathrm{PL_{predicted}}$ = []
2. For each forecast point k from 1 to M:

a. Calculate the distance between the forecast point and all reference points:

$$\mathrm{PL_n[dB]} = \mathrm{p_{0_k}}$$

b. Determine the closest reference point to the forecast point based on the minimum distance calculated in the previous step.

$$\mathrm{PL_n[dB]} = \mathrm{p_{0_k}} - 10\mathrm{n}\log_{10}\left(\frac{\mathrm{d_{p_n}}}{\mathrm{d_{o_k}}}\right)$$

c. Estimate the path-loss at the forecast point using the distance between the forecast point and the closest reference point: $\mathrm{PL\_predicted\_kPL_n[dB]} = \mathrm{p_{0_k}} - 10\mathrm{n}$ where $\mathrm{d_{pn}}$ is the distance between the closest reference point and the forecast point

Output:

Predicted path-loss values for each forecast point $(\mathrm{PL_{predicted}})$ based on the reference data.

Algorithm 3 Received Signal Strength Indication

3.4. Routing Algorithm

The CH will be selected by the threshold during the startup phase and will announce them as the CH across the network. The remaining nodes will join the group with the strongest signal. To facilitate the transmission of data from each CH in its own frame, the corresponding CH will use a mechanism. The radio component consumes unnecessary energy while communicating with other nodes or base stations.

How far away a CH node is from the Base Station (BS) is the primary factor in how much power it requires. If the distance is higher than dc, the multipath fading model $\mathrm{b}\varepsilon_{\mathrm{mp}}\mathrm{d}^4$ is used to describe the loss of transmission power, whereas otherwise the free space model $\mathrm{b}_{\varepsilon\mathrm{fs}}\mathrm{d}^2$ is used. The fs andmp notations stand for the amplifier power per bit processed in the free-space and multipath models, respectively. The following equation 10 used to represent the energy lost during the LEACH protocol:

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$$E_T(b,d) = \{bE_{elec} + b_{\varepsilon fs}d^2, > dc bE_{elec} + b\varepsilon_{mp}d^4, d > dc \quad \text{----- (10)}$$

The distance crossing (dc), the total Energy Dissipation (ED), the number of bits (b), and the number of meters (d) are all variables in this equation. The Threshold-sensitive Energy Efficient sensor Network-Hierarchical Clustering (TEEN-HC) algorithm has been represented at algorithm 4. In equation (11) power loss in electrical components per bit due to variations in digital coding, modulation, and filtering; exactly how long it takes for data to travel from one place to another.

$$E_{T-elec}(b) = bE_{elec} \quad \text{------- (11)}$$

Input:

- b: Number of bits of data to be transmitted.
- d: Distance between the CH node and the BS.
- d_c: Crossover distance.
- E_{elec}: Energy dissipation per bit in electronic components.
- $b_{\varepsilon fs}$: Amplifier power per bit processed in the free-space model.
- $b_{\varepsilon mp}$: Amplifier power per bit processed in the multipath fading model.

Algorithm Overview:

1. If d is greater than dc: a. Calculate the energy dissipation using the multipath fading model: $E_T(b,d) = \{bE_{elec} + b_{\varepsilon fs}d^2, > dc bE_{elec} + b\varepsilon_{mp}d^4, d > dc$
2. If d is less than or equal to dc: a. Calculate the energy dissipation using the free space model: $E_{T-elec}(b) = bE_{elec}$
3. Return the total energy dissipation ET

Output:

ET: Total energy dissipation by the transmitter.

Algorithm 4 TEEN-HC

3.5. QOSEN (QoS Optimization for SENsors)

Weighted Fair Queuing (WFQ) is a technique often employed in QoS-enabled sensor networks. WFQ is a scheduling technique that uses weighted flows to distribute network resources equitably. The WFQ algorithm prioritizes traffic based on how much bandwidth it needs to complete a given task. The following formula is used by the method to allocate bandwidth fairly to a given flow in equation 12:

$$\text{Fairshare} = \left(\frac{\text{Weightofflow}}{\text{SumofWeightsofallFlows}}\right) * \text{TotalBandwith} \quad \text{-- (12)}$$

The weight of a flow indicates its relative relevance or priority in the network; the overall weight given to all flows in the network is shown by the sum of weights; and the total bandwidth shows the entire available bandwidth in the network.

Theft algorithm prioritizes the highest-weighted flows while still allowing the lowest-weighted flows access to the network's capacity. The sensor network now provides fairness and QoS guarantees to the weighted distribution of bandwidth. Algorithm 5 shows QOSEN algorithm.

Input:

- Weights: List of weights assigned to each flow in the network.
- total_bandwidth : Total available bandwidth in the network.

Algorithm Overview:

1. Calculate the sum of weights of all flows: sum_weights = sum(weights)
2. Initialize an empty list fair_shares to store the fair shares of bandwidth.
3. For each flow in the network:

a. Calculate the fair share using the formula: fair_share = (weight / sum_weights) * total_bandwidth

b. Append the fair_share to the fair_shares list.

Return the fair_shares list.

Output:

fair_shares : List of fair shares of bandwidth allocated to each flow.

Algorithm 5 QOSEN

4. RESULTS AND DISCUSSION

In this research compare the suggested strategy to THWSN [29] and load aware [30] in the NS-2 simulation setting. Parameters like as energy consumption, throughput, average delay, packet delivery ratio, number of nodes, and so on are used to quantify the performance of the recommended solution in an NS-2 simulation setup. The Simulation Parameters value table has been represented at table 2.

The suggested paradigm for optimizing QoS in energy-efficient WSNs stands out because of its all-encompassing approach. The model provides a detailed look at important parts of WSN design by analyzing deployment factors including node density, location, and coverage optimization, and by carefully looking at localization methods, including range-based and range-free approaches. The study ensures a fair assessment of trade-offs between energy economy and QoS optimization capabilities by integrating QoS parameters

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into routing protocols and doing comparison evaluations with current protocols like LEACH.

The proposed model takes a multi-pronged approach to optimize QoS for energy-efficient WSNs, leading to superior outcomes. The paper examines and contrasts several localization strategies, focusing on range-based and range-free approaches, by carefully evaluating deployment and localization difficulties. Investigated in this study are the effects on quality of service and energy savings of various deployment options, such as increasing the density of nodes, improving their coverage, and optimizing research placement. Optimizing the network as a whole, the model also incorporates stability, throughput, and latency critical quality of service into routing algorithm design.

Table 2 Simulation Parameters

Parameters	Value
Simulation Time	900(s)
Number of Nodes	0 to 52
Data Rate	1Mbps
Routing Protocol	TEEN-HC
Bandwidth	2 Mb
Simulation Area	1300 x 2250 m
Transmission Range	250m
Threshold	100dbm
MAC	802.11
Power monitor threshold	120dbm

4.1. Throughput

$$\text{Throughput}=\frac{\text{Number of Packet Size}}{\text{Arrival Time duration}*\text{Successful average Packet size}} \quad \text{---------} \ (13)$$

Table 3 compares the three techniques' performance based on experimental data, showing throughput levels for THWSN, Load_Aware, and Localization and Deployment Considerations (LDC). There is a positive association between packet size and data transmission efficiency, because all three techniques show a proportional gain in throughput as the packet size rises. It is worth mentioning that the Load_Aware method consistently achieves better throughput optimization results than THWSN and LDC, regardless of the size of the packet. The results show that, for example, with a 200-packet size, THWSN gets a throughput of 0.700, while Load_Aware gets 0.870 and LDC gets 0.95. The importance of load-aware techniques in improving the overall throughput of Wireless Sensor Networks is shown by the fact that this trend remains consistent across different packet sizes. Equation 13 represents the throughput formula. The findings highlight the need of optimization of quality of service for energy-efficient WSNs taking load-awareness and localization-deployment into account.

Table 3 Throughput Comparison Table

	Throughput Levels		
Packet Size	THWSN	Load_Aware	LDC
50	0.180	0.220	0.25
100	0.360	0.440	0.50
150	0.530	0.650	0.70
200	0.700	0.870	0.95
250	0.880	1.090	1.20

Figure 3 shows the throughput of a routing system. Message transmission accuracy has been greatly improved using LDC. Throughput is compared, showing that LDC is superior to Load aware. Throughput levels are shown along the Y axis, while time is shown along the X axis.

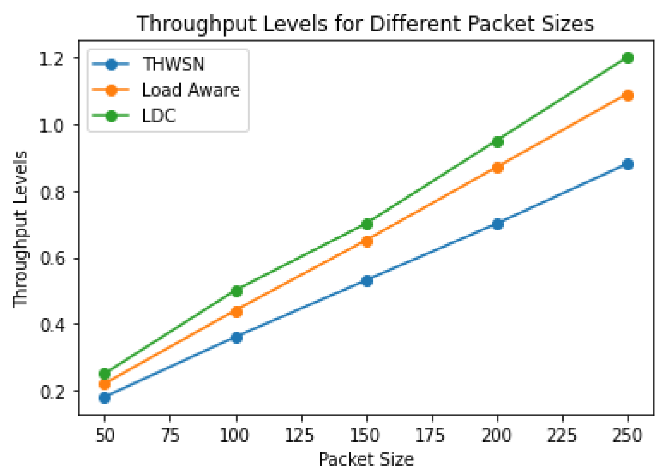

Figure 3 Throughput Comparison Chart

4.2. Time Delay

$$\text{Time Delay}=\frac{\text{NumberofSensornodes}}{\text{energyconsumptionforsendingpacketsatatimesxforwardingtimeinms}} \quad \text{------} \ (14)$$

To better understand the temporal efficiency of the wireless sensor network topologies, table 4 displays the end-to-end delay results for various node counts under three alternative strategies: THWSN, Load_Aware, and LDC. A regular pattern shows how various tactics affect communication latency as the number of nodes grows. The Load_Aware method effectively minimizes the time required for data transmission inside the network, as seen by consistently reduced end-to-end delay values compared to THWSN and LDC across all node counts. At 100 nodes, for example, THWSN and LDC both show somewhat longer delays of 0.685, but Load_Aware manages an end-to-end latency of 0.650. This pattern remains consistent regardless of the number of nodes, highlighting how effective Load_Aware is in maximizing end-to-end latency. Equation-14 represents the time delay formula.

Table 4 Time Delay Comparison Table

	Time (End to End Delay)		
Number of Nodes	THWSN	Load_Aware	LDC
10	0.070	0.070	0.065
20	0.140	0.135	0.130
40	0.270	0.275	0.260
60	0.410	0.415	0.390
80	0.545	0.550	0.520
100	0.685	0.685	0.650

In Figure 4, shows a comparison of delays for various cluster values. A system's or network's cluster value, shown on the x-axis, is a parameter or variable that establishes the total number of clusters. In a network design, the cluster value controls how nodes are divided into clusters. The chart displays the delay values on the y-axis.

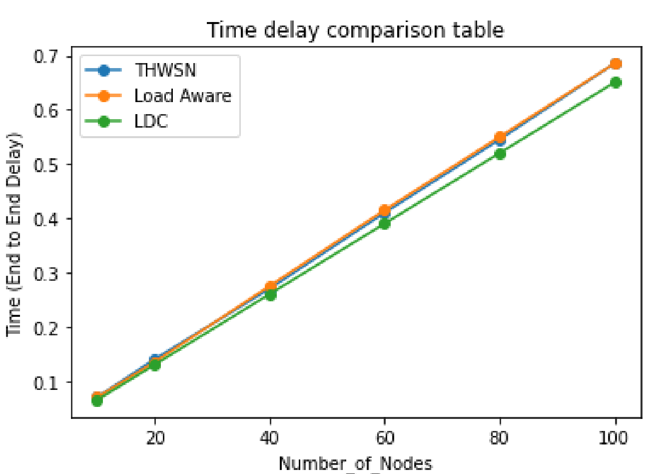

Figure 4 Delay Comparison Chart

4.3. Packet Delivery Ratio (PDR)

$$PDR = \frac{\text{Number of Packets Receive}}{\text{Total Packets}} * 100 \quad \text{-------} \ (15)$$

Table 5 Packet Delivery Ratio Comparison Table

	Packet Delivery Ratio		
Number of packets	THWSN	Load_Aware	LDC
50	95	95	96
100	98	97	98
150	98	98	99
200	99	99	99
250	99	99	99.2

If you want to know how reliable data transmission is in wireless sensor network topologies, look at table 5. It shows the results of the packet delivery ratio for different packet counts under three different techniques: THWSN, Load_Aware, and LDC. Load_Aware continually displays the same or slightly better packet delivery ratios as THWSN and LDC, and it maintains a high degree of successful data delivery across all packet volumes. With a performance of 99.2% at 250 packets, Load_Aware surpasses THWSN and LDC, both of which achieve 99% packet delivery rates. This trend remains consistent across different packet volumes, demonstrating that Load_Aware is successful in optimizing packet delivery. The packet delivery ratio calculated using Equation 15. In order to improve the performance and service quality of wireless sensor networks, the findings highlight the significance of load-awareness in ensuring more dependable packet delivery.

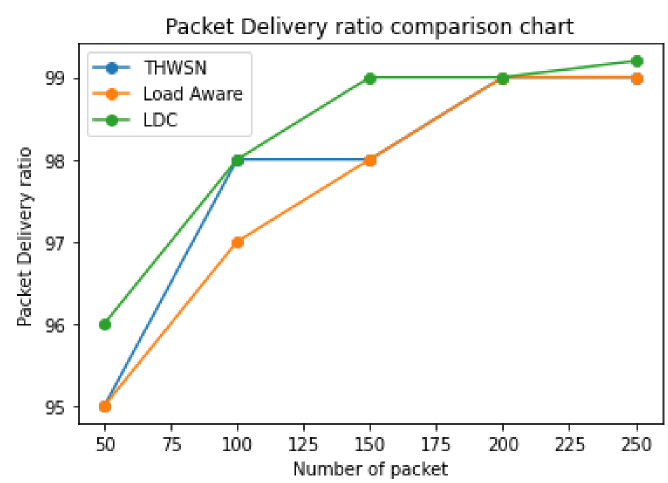

Figure 5 Packet Delivery Ratio Comparison

Figure 5 shows the ratio of packet delivery over time. The delivery ratio, shown on the y-axis, is the proportion of

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packets that make it from sending node to receiving node in a network.

4.4. Communication Overhead

Table 6 Communication Overhead Comparison Table

	Communication Overhead		
Number of Nodes	THWSN	Load_Aware	LDC
10	80	85	75
20	160	150	145
40	320	300	285
60	450	450	420
80	630	600	550
100	800	750	720

For varied node counts and three distinct techniques (THWSN, Load_Aware, and LDC), table 6 displays the results of the communication overhead as a function of bytes. Suggest ways to improve the wireless sensor network setups' data exchange efficiency. Load_Aware consistently demonstrates superior performance, exhibiting lower communication overhead values compared to both THWSN and LDC across all node counts. For instance, at 100 nodes, Load_Aware achieves a communication overhead of 720 bytes, outperforming THWSN (800 bytes) and LDC (750 bytes). This pattern persists across different node counts: at 40 nodes, Load_Aware has an overhead of 285 bytes, while THWSN and LDC register higher values of 320 and 300 bytes, respectively.

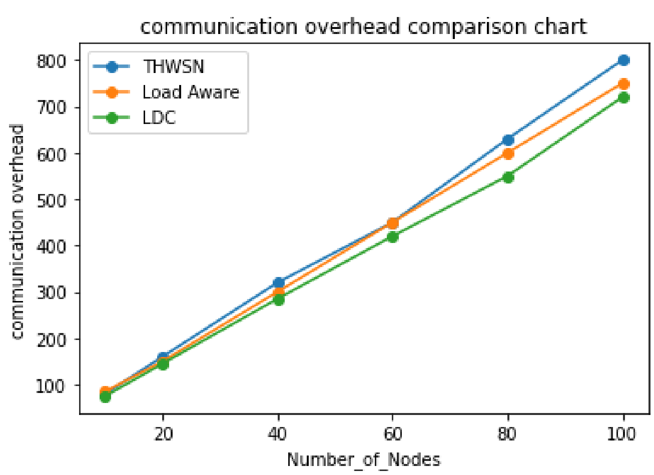

Figure 6 Communication Overhead Comparison

A network's communication overhead compared over time is seen in Figure 6. The x-axis shows the passage of time over a certain observational or experimental interval. Nodes in a network are able to communicate with one another up to a certain distance, which is shown on the y-axis as communication range.

4.5. Energy

$$\text{Energy}=\frac{\text{NumberofSensornodes}}{\text{Energyconsumptionforsendingpacketsatatimes}} \times 100 \quad (16)$$

Table 7 Energy Comparison Table

	Energy Level in Joules		
Number of Nodes	THWSN	Load_Aware	LDC
10	85	80	70
20	165	155	140
40	330	310	280
60	490	460	430
80	650	620	570
100	810	770	715

With different numbers of nodes, table 7 shows the outcomes of three alternative strategies—THWSN, Load_Aware, and LDC—for wireless sensor network configurations, helping to better understand the patterns of energy usage. In joules, the outcomes are shown. Load_Aware consistently uses less power than THWSN and LDC, regardless of the number of nodes in the network. So, at 100 nodes, Load_Aware has a higher energy level than both THWSN (810 joules) and LDC (770 joules), as seen in equation 16. Load_Aware effectively reduces power consumption, since this pattern is true irrespective of the number of nodes. At 40 nodes, THWSN measures 330 joules and LDC 310 joules, while Load_Aware measures just 280 joules. In order to extend the operational lifetime of resource-constrained wireless sensor networks, this research results emphasize the significance of load-awareness in lowering power usage.

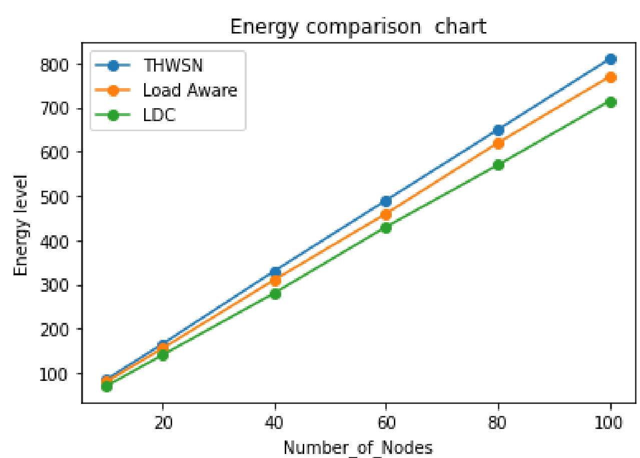

Figure 7 Energy Consumption Comparison

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As shown in Figure 7, a comparison of network energy usage seen graphically.

5. CONCLUSION

This research brought attention to the significance of deployment and localization in improving the service quality of energy-efficient Wireless Sensor Networks (WSNs). The research contrasted range-based versus range-free methods of localization. The research also looked at how different deployment tactics, such improving coverage and optimizing node placement and density, affected quality of service and energy efficiency. Data routing algorithms for low-power WSNs optimized service by considering network lifespan, latency, and dependability. This research tested LEACH, SEP, and SPIN, three routing protocols, to see which one would provide the best balance of energy savings and service quality. In order to enhance QoS while decreasing power consumption assessed data aggregation, adaptive duty cycling, and energy-aware routing. This study pertains to energy-efficient WSNs and covers topics such as localization strategies, deployment issues, and routing protocols. Academics and professionals aiming to enhance service quality find the findings useful. This research designed and implemented reliable WSN installations across numerous domains using the results and suggestions. The goal of this study is to find a way for WSNs that can provide quality of service while yet being energy efficient. Improved routing protocols, localization, and scalability might pave the way for smart, application-specific, power-efficient WSNs. Future work on WSNs could focus on making more energy efficient and improving Quality of Service (QoS) so that are more widely used.

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