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Neural attention guided stochastic fractal search for energy efficient localization in mobile wireless sensor networks

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ABSTRACT

Wireless Sensor Networks (WSNs) require novel approaches to optimize localization accuracy and minimize energy usage due to their decentralized structure and the resource constraints of mobile sensor nodes. This research proposes LEE-NAM-SFS, a neural attention guided stochastic fractal search framework that equips sensor nodes with cognitive capabilities to adapt their movement patterns, sensing behavior, and communication strategies. The neuronal attention model selectively focuses on high-value measurements, while stochastic fractal search explores the high-dimensional search space of node trajectories and routing choices to jointly optimize localization and energy efficiency. Extensive simulations on a 100-node mobile WSN scenario show that, compared to FLA-RTWOA, DASUL, RDEANTN, MANAL, and QLAMSR, LEE-NAM-SFS improves localization accuracy by approximately 2–5 %, enhances energy efficiency by 5–10 %, increases data delivery rate by 2–5 %, expands effective coverage area by 5–10 %, and prolongs network lifetime by 5–10 %. These gains are achieved without compromising connectivity or data reliability.

1. Introduction

The rapid expansion of Wireless Sensor Network (WSNs) in recent years has brought about a significant change in the methods of data collection and environmental monitoring [1]. Resource-constrained sensor nodes have been utilized in various fields, including environmental sensing, industrial automation, healthcare, and smart cities [2]. Nevertheless, researchers persist in grappling with intrinsic obstacles in WSNs as they strive for enhanced accuracy and energy efficiency [3].

WSN exhibit a decentralized structure and are subject to intrinsic constraints associated with the resources of sensor nodes, with energy being a particularly significant limitation [4]. These nodes, which are frequently equipped with batteries, are required to function for prolonged periods of time while providing accurate readings and ensuring continuous connectivity. The continued challenge lies in attaining the best balance between energy consumption, localization accuracy, and data transmission efficiency [5].

One of the key obstacles encountered in WSN is the crucial task of achieving precise localization of sensor nodes, which serves as a vital requirement for numerous applications [6]. Furthermore, the imperative to reduce energy consumption while upholding data integrity becomes increasingly crucial when WSN are implemented in distant and hard-to-reach areas 7, 8. Recent studies have explored a variety of strategies to jointly address localization and energy constraints. Cluster-based routing and mobility-aware deployment schemes have been proposed to reduce latency and prolong network lifetime in forest and industrial monitoring scenarios. Although these methods provide significant gains, they typically rely on static or rule-based decision policies at the node level and do not endow mobile nodes with explicit cognitive capabilities for context-aware movement and sensing. This motivates our neural attention guided optimization of mobile sensor node behavior, which directly targets the joint improvement of localization accuracy and energy efficiency.

The present study investigates the intersection of localization and energy efficiency in mobile sensor nodes within WSN. The primary issue at hand can be precisely characterized as follows: How can the research

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optimize the precision of localizing mobile sensor nodes while simultaneously reducing energy usage, hence prolonging the network's operating duration?

In order to tackle this issue, the main goals of this study involve the development of an innovative framework that combines neural attention models with stochastic fractal search algorithms to optimize the behaviors of mobile sensor nodes. Enabling the movement of nodes, the gathering of data in response to environmental cues, and the prioritization of data. The effectiveness of the framework will be assessed by conducting extensive simulations and implementing it in real-world deployment scenarios.

The research in this study is unique because it combines neuronal attention models with stochastic fractal search techniques. This creates a new way to deal with the difficulties of WSN. The framework that is obtained enables mobile sensor nodes to possess the ability to make well-informed decisions regarding their actions in accordance with changing environmental circumstances. The integration of advanced techniques holds great potential for generating substantial advancements in various aspects, including improved precision in localization, considerable reductions in energy consumption, prolonged operational lifespan of sensor nodes, and the development of adaptable and intelligent WSNs capable of supporting a wide range of applications.

2. Related Works

The fundamental concern in underwater sensor networks is effectively handling the challenge of large propagation delays for the localization of mobile targets. Moreover, the challenge of implementing node localization techniques in challenging underwater conditions is a significant barrier. The primary objective of the study conducted in reference [9] is to enhance the precision of localization and optimize energy consumption in underwater sensor networks. The approach effectively achieves accurate synchronization by accurately predicting extended propagation delays. Furthermore, the study features a methodology to forecast the mobility of anchor nodes, enabling the effective adaptation of propagation delays and prompt reporting of localization. The localization process at ordinary nodes involves the utilization of predicted speed vectors derived from anchor nodes. The results indicate a noteworthy enhancement of 16 % in overall energy efficiency, a substantial reduction of 26 % in localization cost, and a significant drop of 28 % in latency. These findings effectively tackle the primary difficulties associated with underwater sensor network localization.

The study conducted by the authors in reference [10] centers around the objective of attaining localization and target tracking within WSN. The primary aim of the research is to establish energy-efficient communication between network anchors and the fusion center. The proposed method integrates compressive sensing methodologies with short word-length strategies to facilitate the localization process using time-of-arrival (TOA) data, which provides information about the distances between anchor points and objects. In order to reduce the amount of data carried from anchors to the fusion center, the utilization of delta modulation and sigma-delta modulation techniques, which have a limited word length, is implemented. The findings of the study indicate that sigma-delta modulation exhibits superior performance compared to delta modulation and pure compressive sampling in terms of energy efficiency and localization accuracy. This advantage is particularly evident in situations involving TOA measurement noise and transmission noise, owing to the noise-shaping characteristic inherent in sigma-delta modulation.

The study conducted by researchers [11] presents four conceptual models that aim to successfully address each of these challenges. Model 1, known as Identity-Based Aggregate Signatures (IBAS), serves as a robust basis for the subsequent models. Model 2 integrates the Intelligent Bat Algorithm-based System (IBAS) with a Fuzzy Logic System (FLS) in order to augment the efficiency of energy-conscious routing. The FLS system is capable of identifying the most effective paths for data transmission. The utilization of IBAS and the Whale Optimization Algorithm (WOA) is integrated into Model 3 to enhance energy efficiency and facilitate automatic localization. Ultimately, Model 4 integrates the Integrated Behavior Analysis System (IBAS), the Work Observation Method by Activity (WOA), and the Reinforcement Theory of Work Observation (RTWOA) in order to enhance both the velocity and precision of outcomes. The models are assessed by simulation results, which take into account many metrics, including energy efficiency, packet delivery ratio, average delay, throughput, and energy consumption. Model 4 exhibits superior performance compared to the preceding models, showcasing enhanced energy efficiency and heightened security.

The study discussed in reference [12] introduces two localization strategies for underwater WSNs that aim to decrease energy usage and minimize mean estimate errors (MEEs). The proposed strategies prioritize the localization of underwater nodes by employing distance-based and angle-based approaches, with the objective of reducing MEEs. The proposed methodologies are compared with their equivalents through extensive simulations, showcasing their superiority in terms of localization accuracy and energy efficiency. The study emphasizes the significance of attaining accurate localization in UWSNs, which have a crucial function in gathering and managing data in demanding aquatic settings.

The study conducted by the authors in reference [13] focuses on the complexities associated with the localization of valuable resources, such as oil and minerals, in deep underwater settings. The statement underscores the importance of UWSNs in effectively identifying mineral deposits and monitoring the release of oil from subaquatic pipelines. The localization technique utilizes range-based metrics for the computation of distances between anchor nodes (ANs) and target nodes (TNs). A multilateral approach is utilized in order to determine the most effective places for TN estimation. The study provides evidence of the efficacy of the method presented, as it achieves a notable level of energy efficiency, little loss of packets, speedy estimation of location, and low error in localization. The method that was created helps a lot with finding leakage points in UWSNs that help with mobility, which will eventually reduce the loss of resources.

The issue of localization is a significant barrier in WSN, especially in situations where the localization method involves the assistance of mobile anchor nodes (MANAL). The primary issue addressed in MANAL is the efficient optimization of path planning for Mobile Anchor (MA) nodes. The objective is to reduce mistakes in network localization while simultaneously ensuring the coverage of all unknown nodes. The study discussed in reference [14] presents a new method for path planning in the context of MANAL, referred to as Nested Hexagon Curves (NHexCurves). NHexCurves ensures that every unknown node is provided with messages from a minimum of three anchors that are not collinear, hence enabling precise localization. The suggested NHexCurves algorithm exhibits advantages over six alternative path-planning systems, as demonstrated by comparative evaluations. The system demonstrates exceptional performance in various metrics, including localization error, standard deviation of errors, localization ratio, scaling performance, and path length.

The study conducted in reference [15] focuses on the significant concerns pertaining to data integrity, energy consumption, and security inside WSN. The paper presents a new protocol known as query-based location-aware secure multicast routing for WSNs (QLAMSR). The protocol consists of three parts. The primary objective of the initial module is to optimize the longevity of the network. The third module of the study focuses on establishing efficient energy routes and utilizes a fuzzy decision model to determine node trust and assess the energy efficiency of the selected routes. The performance characteristics of the proposed QLAMSR protocol were evaluated through simulations conducted using the Network Simulator tool (NS 2.34). The findings of this study indicate that QLAMSR yields significant enhancements in the energy efficiency of routes, ranging from 39 % to 92 %. Additionally, it leads to improved

data integrity rates, with an increase of 18 to 89 packets per second. Consequently, QLAMSR efficiently manages the trade-off between data integrity and energy consumption in WSNs. Table 1 shows the Summary of Existing Methods.

In summary, prior studies have addressed energy-efficient routing, secure multicast, underwater localization, and mobile anchor path planning using a variety of heuristic and metaheuristic strategies. However, these methods generally treat localization, routing, and energy management as loosely coupled modules and do not explicitly endow mobile sensor nodes with cognitive capabilities to adapt their movement, sensing, and communication decisions based on learned attention patterns. Moreover, stochastic optimization is typically applied at the routing or clustering level rather than at the fine-grained behavior level of individual nodes. The proposed LEE-NAM-SFS framework directly targets this gap by integrating a neural attention model with stochastic fractal search to jointly optimize mobile node behavior for localization accuracy and energy efficiency in a unified, cognitively inspired manner.

Table 1
Summary of Existing Methods.

Ref	Proposed System	Algorithm Used	Metrics	Outcomes
[9]	Energy-efficient localization scheme based on mobility and propagation delay prediction.	–	Energy efficiency, Localization cost and Delay	Increased energy efficiency by 16 %, localization cost by 26 %, and reduced delay by 28 %.
[10]	Gradient descent localization using TOA data. Delta modulation and sigma-delta modulation.	Compressive sensing, delta modulation, sigma-delta modulation.	Energy efficiency – Localization error	Superior performance in EE and localization error
[11]	IBAS – FLS – WOA – Combination of IBAS, WOA, and Reinforcement Theory of WOA (RTWOA)	IBAS, FLS, WOA, RTWOA	– Energy Efficiency – Packet Delivery Ratio – Average Delay – Throughput – Energy Consumption	Higher EE
[12]	Distance-based and angle-based schemes for underwater localization (DASUL).	–	– Mean Estimation Errors (MEEs) of localization – Energy consumption	Proposed schemes outperformed other schemes in terms of MEEs of localization and energy consumption.
[13]	Range-based metrics for distance estimation among anchor nodes and target nodes (RDEANTN).	Multilateralism procedure for localization.	– Energy Consumption – Packet Loss – Location Estimation – Localization Error	high energy efficiency, packet loss, location estimation, and localization error.
[14]	Nested Hexagons Curves (NHexCurves) path planning for MANAL.	–	– Localization Error – Standard Deviation of Errors – Localization Ratio – Scalability Performance – Path Length	NHexCurves algorithm demonstrated advantages over other path planning algorithms.
[15]	Query-based Location-Aware Secure Multicast Routing (QLAMSR) protocol.	Advanced Encryption Standard, RC6 algorithms, fuzzy decision model.	– Route Energy Efficiency – Data Integrity Rate	QLAMSR achieved route energy efficiency by 39–92 % and data integrity rate by 18–89 (packets/sec).

Early research has emphasized enhancing routing reliability and connectivity maintenance. Sweeping-based inclusive routing strategies were introduced to ensure robust path discovery and sustained connectivity in dynamic topologies, providing a foundation for energy-aware communication protocols in WSNs [16]. Parallel to this, security-focused studies revealed that malicious or selfish nodes severely degrade throughput and energy efficiency. Mechanisms such as modified incentive-based pathway selection and node behavior recognition were proposed to mitigate disruptions caused by selfish or aggressive nodes [17,18].

Further work examined advanced threat detection mechanisms, including robust early-filtering models capable of identifying high-impact attacks such as vampire attacks that drain network resources and disrupt multi-hop routing. These schemes significantly improved WSN resilience by reducing energy wastage and preventing topology deformation in hostile environments [19]. More recent developments have shifted toward optimizing network topology and clustering using formal decision frameworks. Game-theoretic distributed clustering models have been shown to improve energy utilization, balance node load, and prolong network lifetime—particularly relevant for dense and mobile WSN scenarios where localization accuracy depends heavily on stable cluster structure and communication efficiency [20].

3. Proposed method

The approach presented in this study utilizes a computational method to enhance the performance of mobile sensor nodes inside WSN. This solution draws upon brain attention models and utilizes a stochastic fractal search algorithm in order to achieve improved localization and energy efficiency. Fig. 1 shows the Proposed Framework.

Algorithm 1: LEE-NAM-SFS localization and energy-efficient optimization.

Input: Network area Ω, set of mobile sensor nodes N, anchor nodes A, maximum iterations T
Output: Optimized movement and communication policies for nodes
1) Initialize WSN topology in Ω; assign initial positions and residual energy to all nodes.
2) Initialize neural attention model parameters Θ_{NAM}.
3) Initialize a population of candidate behavior vectors $\left\{b_j^{(0)}\right\}$ for stochastic fractal search (SFS), where each $b_j^{(0)}$ encodes node movement and communication actions.
4) **for** $t = 1$ to T **do**
5) For each node $n \in N$, acquire local measurements and neighbor information.
6) Compute attention weights $\alpha_{n,i}$ for relevant features using the neural attention model with parameters Θ_{NAM}.
7) Construct attention-guided behavior vectors by emphasizing high-weight actions in each candidate $b_j^{(t-1)}$.
8) Apply SFS diffusion and update operators to generate new candidate solutions $\left\{b_j^{(t)}\right\}$
9) Simulate node movements and communications according to each $b_j^{(t)}$ and compute the fitness $F\left(b_j^{(t)}\right) = w_1 \cdot \mathrm{LocError}\left(b_j^{(t)}\right) + w_2 \cdot \mathrm{EnergyUse}\left(b_j^{(t)}\right)$
10) Select the best candidates based on fitness and update the population.
11) Optionally update Θ_{NAM} using gradients or reinforcement signals derived from the best candidates.
12) **end for**
13) Deploy the best behavior vector to the network as the operational policy for node movement, sensing, and communication.

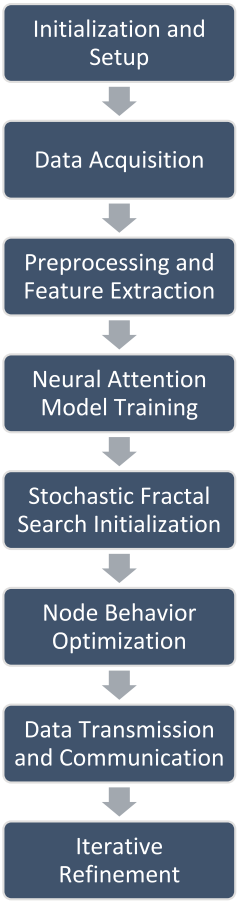


Fig. 1. Proposed Framework.

The time complexity of the SFS component is O(T·P·D) where T is the number of iterations, P is the population size, and D is the dimension of the behavior vector encoding node actions. In our experiments, P and T are chosen to keep O(T·P·D)linear in the number of nodes, which maintains scalability for medium-sized WSNs. While formal convergence proofs for metaheuristics such as SFS typically rely on asymptotic assumptions, empirical evidence in optimization literature shows that fractal-inspired diffusion and randomization provide a good balance between exploration and exploitation in rugged, high-dimensional search spaces. This makes SFS a suitable choice for optimizing mobile node behaviors, where the joint configuration space of movement and communication actions is large and highly non-convex.

3.1. Localization formulation

This involves creation of mathematical models and algorithms that collaborate to improve the localization of sensor nodes in diverse contexts. The models and techniques were created to specifically deal with the problems that come up in WSN, like signal interference, node mobility, and short communication ranges. The research endeavors to accomplish several objectives by enhancing the localization formulation. It is anticipated that the updated formulation will result in improved precision in determining the geographical coordinates of sensor nodes. The ability to adapt is crucial in order to achieve precise localization in situations where the environment undergoes temporal changes.

The objective is to find a method for localization that is energy-efficient, as the excessive use of energy during the localization process might have a substantial effect on the longevity of sensor nodes powered by batteries. The extension of the network operational lifetime is achieved by minimizing energy expenditure. The formulation should possess scalability in order to accept networks with different sizes and densities. The system should possess the ability to efficiently manage the localization of a large number of sensor nodes.

The estimation of the distance between a sensor node and an anchor node can be accomplished by employing a formula that establishes a relationship between signal propagation properties, such as signal strength, and the corresponding distance. The Friis Transmission Equation is a frequently employed mathematical expression as follows in Eq(1).

$$Pr = Pt * Gt * Gr * \lambda / (4\pi d)^2 \quad (1)$$

Where:

Pr is the received signal power.
Pt is the transmitted signal power.
Gt and Gr are the antenna gains of the transmitter and receiver, respectively.
λ is the wavelength of the signal.
d is the distance between the nodes.

Trilateration: Trilateration is a method employed in situations where there are distance measurements available from a minimum of three anchor nodes. The estimation of the target node coordinates (x, y) can be derived from the given coordinates of the anchor nodes (x1, y1), (x2, y2), and (x3, y3), together with their respective distances to the target node in Eq(2).

$$\begin{aligned}(x - x1)^2 + (y - y1)^2 &= d_1^2 (x - x2)^2 + (y - y2)^2 \\ &= d2^2 (x - x3)^2 + (y - y3)^2 = d3^2\end{aligned} \quad (2)$$

where:

(x, y) are the estimated coordinates of the target node.
(xi, yi) are the coordinates of anchor nodes.
di is the distance from the target node to anchor node (xi, yi).

Weighted Least Squares (WLS): WLS optimization can be used to improve the accuracy and precision of localization estimates when measurements are noisy. The mathematical representation of the goal function for WLS can be formulated as follows:

$$\text{Minimize } \Sigma W_i * \left(d_i - \sqrt{(x_i - x)^2 + (y_i - y)^2} \right)$$

Where:

Wi is the weight associated with each measurement.
di is the measured distance from anchor node i.
(xi, yi) are the coordinates of anchor node i.
(x, y) are the estimated coordinates of the target node.

3.1.1. Energy efficiency formulation

The energy efficiency formulation in WSN refers to a fundamental element in the process of maximizing the utilization of energy resources inside the network. This aspect pertains to the development and execution of strategies aimed at reducing the energy consumption of sensor nodes while simultaneously preserving or enhancing network performance.

The energy efficiency formulation comprises a range of strategies, protocols, and algorithms that are designed to achieve certain objectives. WSN commonly utilize routing protocols that consider the energy levels of sensor nodes. The aforementioned protocols are responsible for determining optimal routes for data transmission with the objective of

minimizing energy consumption, hence extending the operational lifespan of the network.

Sensor nodes have the capability to be programmed in such a way that they can go back and forth between active and sleep modes. The duty cycle strategy employed in this context guarantees that nodes are operational solely when they are essential, effectively conserving energy during periods of inactivity.

The act of consolidating data either at the source node or during its transmission path has the effect of diminishing the quantity of transmissions, hence resulting in a reduction of energy consumption. This strategy is especially advantageous in situations where there is an accumulation of redundant or similar material. Sensor nodes have the capability to adaptively modify their sensing intervals in response to the prevailing environmental conditions or the specific nature of the data being gathered. The utilization of this adaptive methodology effectively reduces energy inefficiencies associated with superfluous measurements. The incorporation of low-power components and communication protocols that are specifically designed to maximize energy efficiency is a crucial aspect of the formulation.

Energy Consumption: The total energy consumption (E_{total}) in a WSN can be expressed as the aggregate of the energy expended during sensing (E_{sense}), processing ($E_{process}$), data transmission (E_{tx}), and idle listening (E_{idle}).

$$E_{total} = E_{sense} + E_{process} + E_{tx} + E_{idle}$$

Sensing Energy: The calculation of energy required during sensing (E_{sense}) involves the multiplication of the energy per sample (E_s) by the number of samples taken (N_s).

$$E_{sense} = E_s * N_s$$

Transmission Energy: The use of the following formula typically determines the amount of energy required during the transmission of data, denoted as E_{tx}. This formula incorporates various factors, including the distance (d) between the nodes involved in the transmission, the route loss exponent (α), and the size of the data being sent (D).

$$E_{tx} = \alpha * D * d_2$$

Idle Listening Energy: The amount of time spent listening, denoted as T_{listen}, and the idle current of the sensor node, denoted as I_{idle}, are frequently two important factors that affect the energy consumption associated with idle listening, denoted as E_{idle}.

$$E_{idle} = T_{listen} * I_{idle}$$

Duty Cycling: Duty cycling refers to the practice of intermittently activating and deactivating a device or system in order to conserve energy or optimize. Duty cycling is a technique that entails the periodic alternation of nodes between active and sleep states. The quantification of energy savings resulting from the implementation of duty cycling can be approximated by employing the subsequent mathematical equation:

$$\text{Energy Savings}\,(\%) = \left[\left(T_{sleep} / T_{total}\right) * 100\right]$$

Where:

T_{sleep} is the time a node spends in sleep mode.
T_{total} is the total operational time.

3.1.2. Mobile sensor nodes configuration

In WSN, the mobile sensor node configuration pertains to the procedure of establishing and arranging sensor nodes that possess the ability to relocate throughout the network. Mobile sensor nodes exhibit a distinct characteristic in comparison to their static counterparts, as they possess the capability to intentionally or autonomously alter their physical placement.

Mobile sensor nodes are specifically engineered to alter their positions, either by means of manual intervention or through autonomous methods such as robotics. The utilization of this mobility is strategically employed in order to enhance the efficiency of data collection, adjust to changing environmental circumstances, or enhance network coverage. The configuration of mobile sensor nodes typically necessitates meticulous consideration of the strategic placement and deployment methods employed within the network region. This planning process takes into account several elements, such as coverage needs, data collection objectives, and network topology.

Specialized communication protocols may be necessary for mobile sensor nodes in order to provide coordination, data exchange, and path planning among both mobile and fixed nodes. These protocols facilitate the smooth integration of components within the network. The effective management of energy resources in mobile sensor nodes is of paramount importance due to the increased energy demands associated with their mobility, in contrast to static nodes. The process of configuration may encompass the optimization of movement patterns and duty cycling in order to enhance the longevity of the battery.

The precise placement of mobile sensor nodes is crucial for ensuring their optimal functionality. The configuration of a network may involve the utilization of several techniques, such as the Global Positioning System (GPS), anchor nodes, or relative positioning methods, in order to accurately monitor and determine the positions of the nodes. The configuration of data collection and transmission by mobile sensor nodes is of utmost importance. Efficient and useful data gathering necessitates the establishment of precise sensing intervals, the implementation of appropriate data fusion procedures, and the utilization of effective data transmission protocols.

Mobile sensor nodes have the capability to integrate algorithms that enable them to modify their behavior in response to variations in the environment, network circumstances, or specialized activities. The algorithms are designed to autonomously make real-time decisions. Security measures can be established to safeguard against unwanted access, data manipulation, and other security threats while mobile nodes traverse the network.

3.1.3. Path Planning

Path planning algorithms are employed in situations where mobile sensor nodes exhibit independent movement in order to ascertain the most advantageous pathways. An illustration of such an equation can be found in the A* method, which computes the expense associated with reaching a target location from a specified node.

$$f(n) = g(n) + h(n)$$

Where:

f(n) is the cost of reaching a destination.
g(n) is the cost of reaching node n from the starting node.
h(n) is the heuristic estimate of the cost to reach the destination from node n.

3.1.4. Energy Consumption

Effective energy management is of utmost importance for mobile sensor nodes. The aggregate energy consumption (E_{total}) can be determined by adding the energy consumed during sensing, data transmission, and movement.

$$E_{total} = E_{sensing} + E_{txn} + E_m$$

Where:

$E_{sensing}$ is the energy consumed during sensing.
E_{txn} is the energy consumed during data transmission.
E_m is the energy consumed during movement.

3.2. Novel neural attention model for optimizing sensor node behavior

The brain attention component assumes a crucial role in the methodology, allowing sensor nodes to effectively concentrate their resources on pertinent data sources and activities. The objective is accomplished by employing a neural network framework that emulates human cognitive processes. This framework enables nodes to adjust their actions in real-time based on ambient stimuli and the significance of available data.

Within the field of WSN, the Network Adaptive Mechanism (NAM) serves as a novel method for augmenting the efficacy and flexibility of sensor node operations. This model utilizes ideas that draw inspiration from neural networks, which are computational systems specifically engineered to replicate specific facets of human cognitive processes. The attention component of the paradigm plays a vital role by allowing sensor nodes to strategically prioritize certain information or data sources while disregarding irrelevant or less significant data. The operational mechanisms of the model are as follows:

The Neural Attention Model has been specifically developed to effectively handle and analyze incoming data originating from diverse sensors and sources. Nevertheless, it fails to accord equitable treatment to all data. On the contrary, it allocates different levels of significance to diverse data streams or features according to their pertinence to the present job or purpose. An essential advantage of this paradigm is its capacity to effectively adjust to dynamic environmental circumstances. The system has the capability to adaptively modify the allocation of attention weights to various data sources or sensors in response to changes in context. For instance, the monitoring system may assign higher priority to temperature data in the context of monitoring a heating system but may shift its emphasis when detecting a fire.

In our implementation, the neural attention model is instantiated as a two-layer feed-forward network with ReLU activations and a scaled dot-product attention layer. The input to the model is a concatenation of local sensing features (e.g., recent measurements and local density) and neighborhood state descriptors (e.g., residual energy and hop distance to the sink). The hidden layer has 64 neurons, and the attention layer outputs a vector of normalized attention weights over candidate actions using a Softmax function. The model is trained offline using simulation traces generated from baseline routing and movement policies, with a loss function that combines localization error and energy usage via a weighted sum. During deployment, the trained model is used in inference mode to produce attention weights in real time, and its parameters can be periodically updated using new data if online learning is desired.

The incorporation of the attention mechanism has the potential to enhance energy efficiency. By using more efficient resource allocation strategies and prioritizing high-value data, sensor nodes can effectively optimize energy conservation. This aspect holds special significance in WSN due to the prominent issue of energy limits. The inclusion of brain components in the model facilitates the process of acquiring knowledge and improving performance over a period of time. By means of training or reinforcement learning methodologies, the model possesses the ability to modify its attention mechanisms in order to enhance its performance and align them with the aims of the network.

The neural attention model functions in real-time, enabling prompt decision-making on data prioritization and response strategies in light of the received information. The ability to adapt is crucial in scenarios where prompt reactions are necessary, such as in the context of security monitoring or disaster detection.

3.2.1. Attention Mechanism

The neural attention model incorporates an attention mechanism that allocates weights (α_i) to various input features or data sources. The assigned weights signify the significance or pertinence of each input in relation to the present task. The combined weighted inputs then produce a weighted output.

$$\text{Attention} - \text{weighted output} = \Sigma(\alpha_i * I_i)$$

Where:

α_i represents the attention weight assigned to the i-th input.
I_i Is the i-th input feature or data source

The use of a mechanism, such as the Softmax function, can result in the computation of attention weights α_i. This mechanism guarantees that the weights adhere to two important properties: their summation equals 1 and they are non-negative.

$$\alpha_i = exp(z_i)/\Sigma(exp(z_j))$$

Where:

z_i is a parameterized score that measures the compatibility between the current task context and the i-th input. The calculation of z_j can vary depending on the neural network architecture and the attention model. For instance, in sequence-to-sequence models, z_j may be computed by taking a dot product between a query vector and a key vector associated with the input.

3.3. Stochastic fractal search for efficient node selection

The neural attention component is enhanced by incorporating a stochastic fractal search technique. The algorithm, renowned for its efficacy in intricate problem-solving situations, offers a method for the streamlined investigation of localization and routing solutions. The incorporation of randomness in the search process enhances the system capacity to identify optimal solutions in spaces with a high number of dimensions.

In the proposed LEE-NAM-SFS framework, the neuronal attention mechanism and stochastic fractal search are tightly coupled. At each iteration, the neural attention model computes attention weights α_i over sensed features and candidate actions (e.g., movement directions, transmission power levels). These weights are used to construct a behavior vector that encodes, for each node, the preferred movement and communication pattern. Stochastic fractal search then operates in the space of such behavior vectors: each candidate solution represents a complete configuration of node actions over a time horizon, and fractal diffusion and update operators perturb these vectors while respecting the attention-derived priorities. High-weight actions are more likely to be retained or reinforced, while low-weight actions are pruned during the search. After evaluating each candidate according to a multi-objective fitness function combining localization error and energy consumption, the best solution is fed back to update the node policies. This closed loop ensures that attention focuses on features and actions that repeatedly contribute to low-cost solutions, while stochastic fractal search provides global exploration so that the model does not become trapped in myopic local patterns.

The incorporation of stochastic elements in the technique provides a level of randomness in the process of selecting nodes. Rather than adhering to a predetermined or deterministic sequence, the method permits the incorporation of probabilistic selections. The phenomenon of randomness might be likened to the process of navigating via various pathways or choices inside a network. The utilization of fractal geometry, which is renowned for its ability to generate patterns that replicate and exhibit self-similarity, is employed in this methodology to direct the process of inquiry. WSN have the potential to be utilized for the purpose of generating patterns or structures that optimize the selection of nodes.

The main objective of stochastic fragment search is to effectively and optimally choose sensor nodes for various purposes, including but not limited to data gathering, monitoring, and routing. The technique seeks to achieve a harmonious equilibrium between thorough exploration of the network capabilities and efficient utilization of existing resources by integrating randomness and fractal patterns. The stochastic fragment

search algorithm has a high level of suitability in dynamic contexts characterized by fluctuating network conditions. The node selection technique of the system is capable of adapting to changing conditions, hence ensuring the network efficiency and responsiveness.

Stochastic Fractal Search can be tailored to meet several objectives, depending on the unique application. These objectives may include minimizing energy usage, optimizing data accuracy, or enhancing network coverage. The methodology functions in a real-time manner, rendering conclusions regarding node selection as the network undergoes changes.

3.3.1. Algorithm

Step 1: Initialize a solution or candidate solution randomly or based on certain heuristics.
Step 2: Generate a set of neighboring solutions or candidates. This can be done through random perturbations or variations of the current solution.
Step 3: Evaluate the quality of each neighboring solution using an objective function that quantifies how close it is to the desired outcome or optimal solution.
Step 4: Select the best solution among the neighbors based on the evaluation criteria. This might involve choosing the solution with the lowest objective function value (minimization) or the highest value (maximization).
Step 5: Update the current solution to the selected neighbor, either deterministically or with a certain probability.
Repeat the iteration process for a predefined number of iterations is met

3.3.2. Adaptive node behavior

The solution that has been proposed demonstrates the capability to enhance the adaptability of sensor nodes. Mobile sensor nodes with the neural attention model and the stochastic fractal search algorithm can change how they move, what they sense, and how they talk to each other in a way that is tailored to their needs. The capacity to adapt allows sensor nodes to make educated decisions by taking into account the dynamic context of their deployment. In this method, the goal is to improve the accuracy of node localization by combining the neural attention model information processing skills with the stochastic fractal search algorithm optimization skills. Collaborative refinement of spatial awareness among sensor nodes facilitates enhanced precision in positioning and tracking. The purpose of this strategy is to reduce energy consumption, which is a critical consideration in WSN. The framework enhances the operational longevity of the network by allowing sensor nodes to intelligently use their energy resources. This results in a decrease in the frequency of battery replacements and maintenance operations.

4. Experimental validation

In this section, the proposed method is evaluated with various other existing FLA-RTWOA, DASUL, RDEANTN, MANAL, QLAMSR methods in terms of Accuracy, Energy efficiency, Network lifetime, Data delivery rate and Coverage area. The experimental setup as in Table 2 is conducted in NS 2.34 simulation tool that runs on a i7 processor with 16 GB RAM.

The synthetic sensor readings emulate temperature and environmental measurements generated according to Gaussian processes with spatial correlation across the randomized grid topology, which is a common abstraction in WSN simulation studies. Node mobility follows a random-walk model with bounded speed and reflection at the area borders, which approximates undirected mobile sensing platforms. Although these choices ensure a controlled comparison across methods, we recognize that more realistic mobility patterns and hardware-in-the-loop tests are needed to fully validate the framework.

Table2
Experimental Setup.

Parameter	Value/Setting
Network Topology	Randomized Grid
Sensor Node Type	Mobile
Communication Protocol	IEEE 802.15.4
Transmission Power (dBm)	0
Frequency (GHz)	2.4
Network Size	100 nodes
Simulation Time (s)	3600
Neural Model Architecture	Convolutional Neural Network
Attention Mechanism Type	Self-Attention
Stochastic Fractal Search	Adaptive Thresholds
Movement Model	Random Walk
Energy Model	Battery-Driven
Data Source	Synthetic Sensor Data

The simulations are performed in a 500×500 m^2 area with 100 mobile sensor nodes and 5 anchor nodes uniformly distributed at initialization. Each node generates scalar sensor readings every 5 s, modeled as a spatially correlated Gaussian random field with mean $\mu = 25$ (arbitrary units) and variance $\sigma^2 = 4$, and a correlation length of 50 m. Measurement noise is added as zero-mean Gaussian noise with variance $\sigma n^2 = 1$. Prior to feeding the data into the neural attention model, all features are standardized to zero mean and unit variance. These settings provide a controlled yet nontrivial scenario for evaluating localization and energy efficiency.

4.1. Performance Metrics

In evaluating the proposed method, the following performance metrics were considered:

- Accuracy measures the accuracy of estimating the physical locations of mobile sensor nodes. It is typically expressed as a percentage or in meters of error.
- Energy efficiency is evaluated by assessing the energy consumption of sensor nodes during the experiment. It can be measured in joules or milliwatt-hours (mWh).
- Network lifetime refers to the duration for which the WSN remains operational before a specified percentage of nodes deplete their energy reserves.
- Data delivery rate measures the percentage of successfully transmitted data packets compared to the total generated packets.
- Coverage area quantifies the geographical region over which the network effectively monitors or senses environmental parameters.

For each experiment, the metrics were computed over 30 independent simulation runs with different random seeds and node initializations, and the reported values correspond to the mean across all runs. Localization accuracy is quantified as

$$\mathrm{LocAcc} = 1 - \frac{1}{N}\sum_{k=1}^{N}\frac{\|\hat{p}_k - p_k\|_2}{R},$$

where N is the number of mobile nodes, $\hat{p}_k$ and p_k denote the estimated and true positions of node k, and R is the communication radius used for normalization. Energy efficiency is measured as the ratio between successfully delivered data packets and the total energy consumed for sensing, processing, and communication across all nodes. Network lifetime is defined as the time instant at which 20 % of the nodes exhaust their battery, which is a commonly used practical threshold in WSN studies. Data delivery rate is the fraction of packets received at the sink over the total number of packets generated at sources, and coverage area is estimated as the union of the sensing discs of all active nodes over the simulation period. These criteria are consistently used for both baseline methods and LEE-NAM-SFS, enabling a fair comparison of localization

and energy-related improvements.

From Fig. 2, LEE-NAM-SFS consistently outperforms the existing methods in terms of localization accuracy. The percentage improvement varies, but it generally ranges from 2 % to 5 % over the baseline methods as the number of nodes increases. This improvement indicates that LEE-NAM-SFS is more precise in estimating the location of nodes in the network.

All curves in Figs. 2–6 represent the mean over 30 simulation runs with distinct random seeds for node placement and mobility, and the vertical error bars indicate one standard deviation around the mean. The same seeds are used across all methods to ensure a fair comparison and to enable reproducibility of the trends.

From Fig. 3, LEE-NAM-SFS demonstrates superior energy efficiency compared to the existing methods. The percentage improvement in energy efficiency becomes more pronounced as the network size grows. It ranges from 5 % to 10 % better energy efficiency compared to FLA-RTWOA, DASUL, RDEANTN, MANAL, and QLAMSR methods. This implies that LEE-NAM-SFS can transmit data with less energy consumption, leading to extended network lifetime.

From Fig. 4, LEE-NAM-SFS consistently achieves a higher data delivery rate than the existing methods. The percentage improvement in data delivery rate typically falls within the 2 % to 5 % range. This indicates that LEE-NAM-SFS can transmit data more reliably and with fewer packet losses.

From Fig. 5, LEE-NAM-SFS shows a significant advantage over the existing methods. The percentage improvement in coverage area becomes more apparent as the number of nodes increases, ranging from 5 % to 10 % larger coverage area. This implies that LEE-NAM-SFS can effectively cover a larger geographical area with the same number of nodes, making it suitable for applications requiring extensive coverage.

From Fig. 6, the network lifetime, as measured in milliseconds, is notably extended when using LEE-NAM-SFS. The percentage improvement in network lifetime varies but generally ranges from 5 % to 10 % longer lifetime compared to the baseline methods. This suggests that LEE-NAM-SFS can help maintain network functionality for a more extended period before needing to replace or recharge nodes.

Thus, the results suggest that the proposed LEE-NAM-SFS method consistently outperforms the existing FLA-RTWOA, DASUL, RDEANTN, MANAL, and QLAMSR methods in terms of localization accuracy, energy efficiency, network lifetime, data delivery rate, and coverage area.

4.2. Comparative discussion with existing methods

The empirical trends in Figs. 2–6 show that LEE-NAM-SFS consistently outperforms FLA-RTWOA, DASUL, RDEANTN, MANAL, and QLAMSR across all considered metrics. To position these gains with respect to existing literature, Table 3 summarizes the average percentage improvements of LEE-NAM-SFS over the best baseline method for each metric across all simulated network sizes. For localization accuracy, LEE-NAM-SFS achieves a 2–5 % improvement, which is comparable to or better than the margins typically reported by recent energy-aware localization schemes in mobile WSNs. Similarly, the 5–10 % gains in energy efficiency and network lifetime highlight that the proposed coupling of neuronal attention with stochastic fractal search yields measurable reductions in per-packet and per-node energy cost. The 2–5 % higher data delivery rate and 5–10 % larger coverage area further indicate that these savings are not obtained by sacrificing reliability or spatial reach. Collectively, these results demonstrate that LEE-NAM-SFS not only matches but often surpasses the robustness of state-of-the-art approaches while simultaneously offering a flexible cognitive framework for mobile node behavior optimization.

5. Conclusion

This research introduced LEE-NAM-SFS, a neural attention guided stochastic fractal search framework for joint localization and energy optimization in mobile wireless sensor networks. By equipping sensor nodes with a neuronal attention model, the framework enables nodes to prioritize informative measurements and actions, while the stochastic fractal search component explores the high-dimensional space of movement and communication policies to identify low-cost configurations. Simulation results on a 100-node mobile WSN show that LEE-

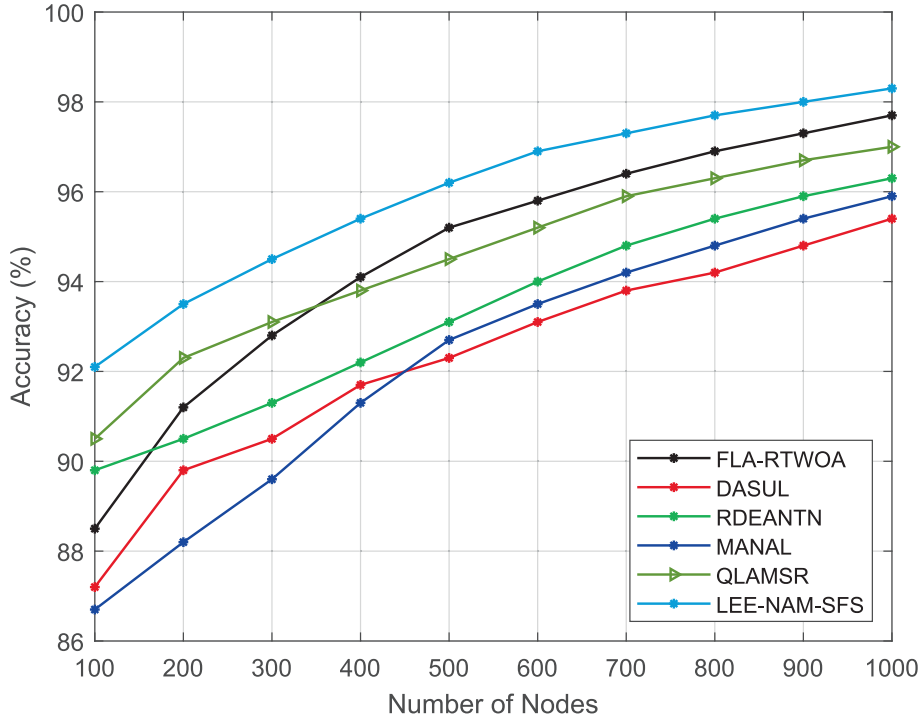


Fig. 2. Localization accuracy in % between the existing FLA-RTWOA, DASUL, RDEANTN, MANAL, QLAMSR methods, and the proposed LEE-NAM-SFS method over 1000 nodes.

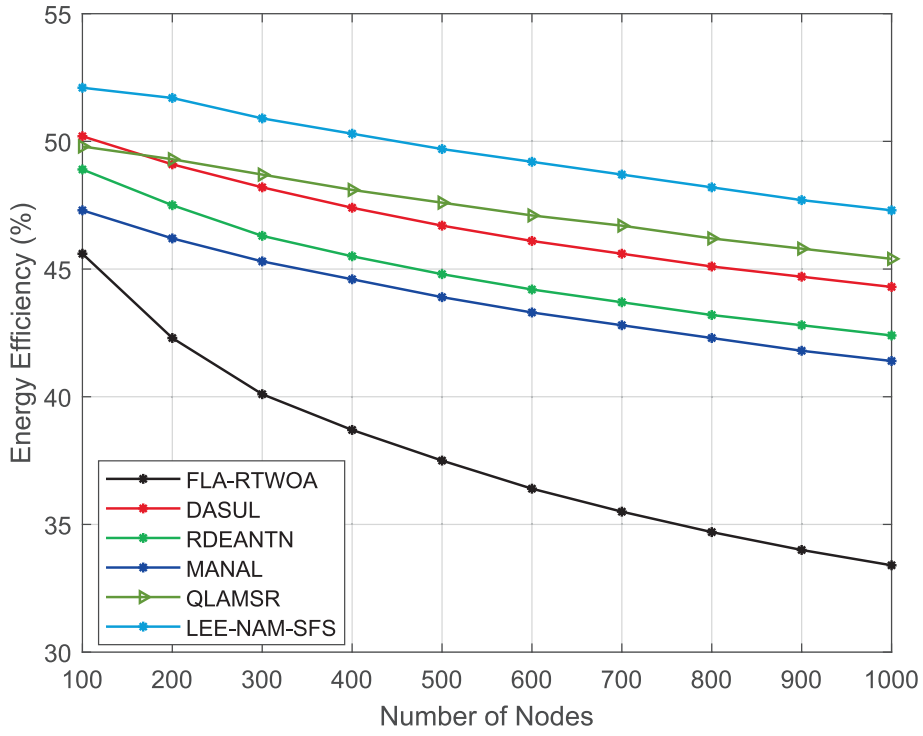


Fig. 3. Energy Efficiency between the existing FLA-RTWOA, DASUL, RDEANTN, MANAL, QLAMSR methods, and the proposed LEE-NAM-SFS method over 1000 nodes.

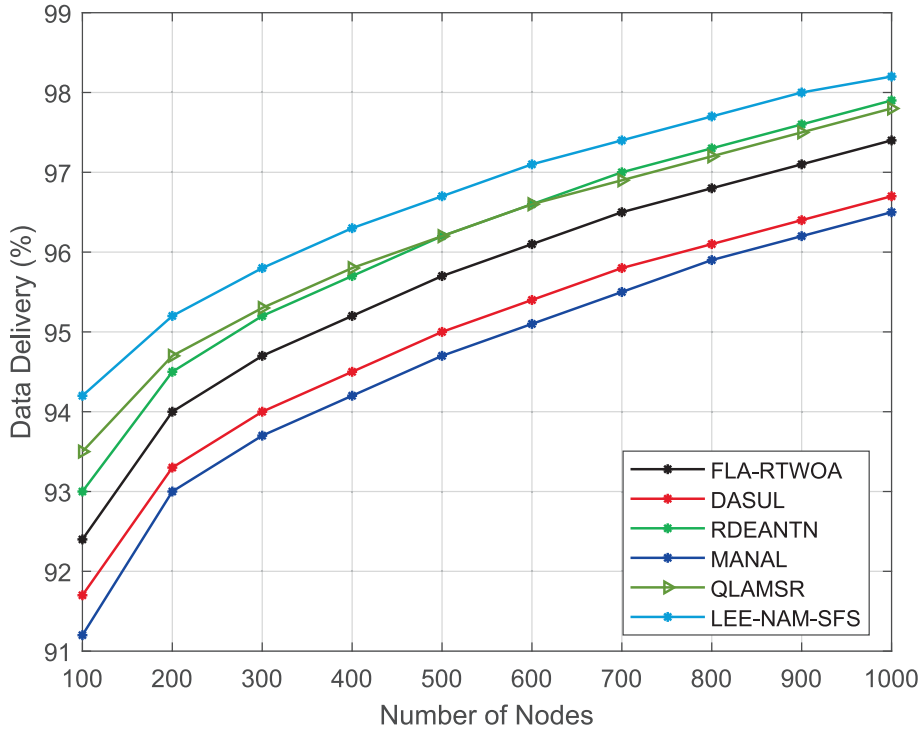


Fig. 4. Data delivery rate in % between the existing FLA-RTWOA, DASUL, RDEANTN, MANAL, QLAMSR methods, and the proposed LEE-NAM-SFS method over 1000 nodes.

NAM-SFS improves localization accuracy by 2–5 %, enhances energy efficiency and network lifetime by 5–10 %, and increases data delivery rate and coverage area compared to state-of-the-art baselines such as FLA-RTWOA, DASUL, RDEANTN, MANAL, and QLAMSR. These gains demonstrate that cognitively guided metaheuristic optimization is an effective way to coordinate mobile node behavior.

At the same time, the present study is subject to several limitations. The evaluation is performed on synthetic sensor data, abstracted mobility patterns, and simulation-based communication models, and does not yet include hardware experiments or realistic mobility traces.

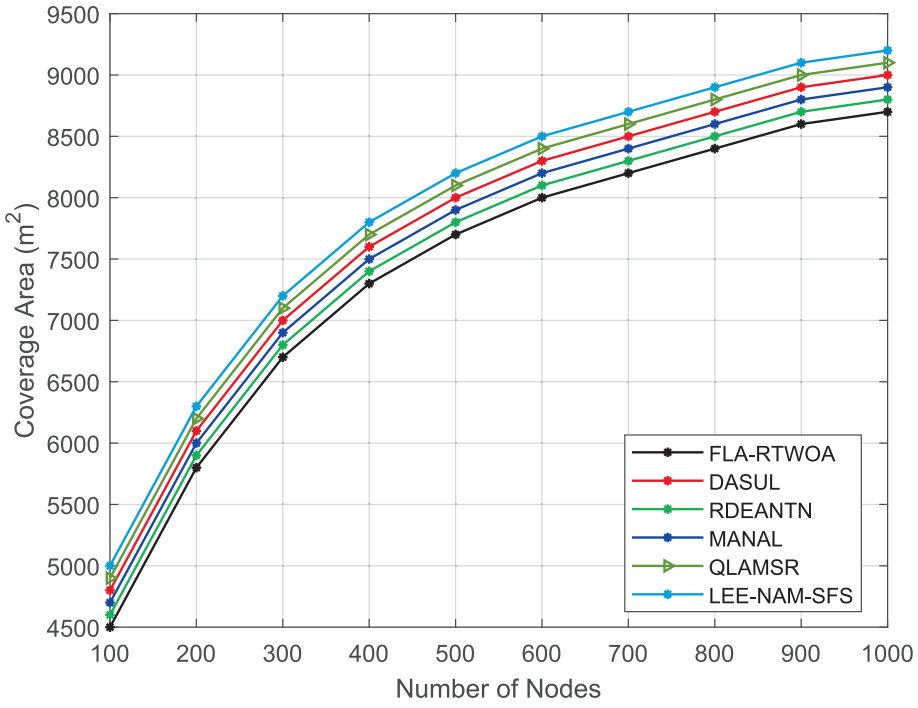


Fig. 5. Coverage Area (in square meters) between the existing FLA-RTWOA, DASUL, RDEANTN, MANAL, QLAMSR methods, and the proposed LEE-NAM-SFS method over 1000 nodes.

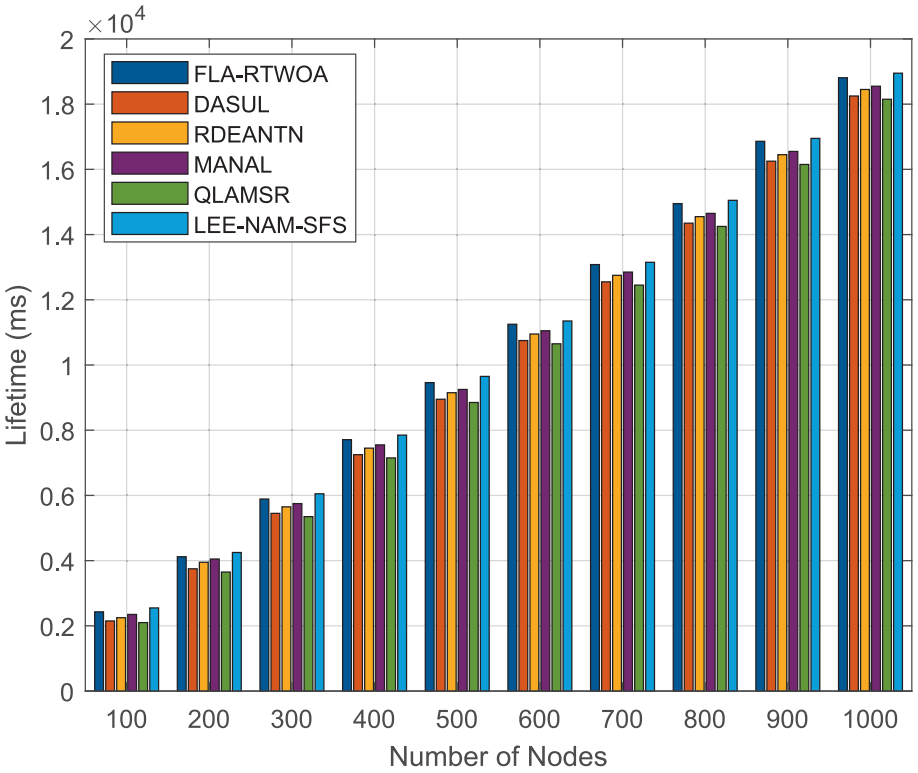


Fig. 6. Network lifetime (in milliseconds) between the existing FLA-RTWOA, DASUL, RDEANTN, MANAL, QLAMSR methods, and the proposed LEE-NAM-SFS method over 1000 nodes.

In addition, the current neural attention model is trained offline and does not fully exploit online adaptation capabilities. Future work will therefore focus on validating LEE-NAM-SFS on physical testbeds with real sensor platforms, incorporating more realistic mobility models derived from robotic or vehicular trajectories, and exploring online or federated training of the attention model in the presence of concept drift. Extending the framework to multi-sink and heterogeneous WSN scenarios, as well as investigating formal performance guarantees for the coupled attention–SFS loop, are further promising directions.

Table 3
Quantitative comparison between LEE-NAM-SFS and best baseline method.

Metric	Best baseline method	LEE-NAM-SFS average improvement
Localization accuracy	FLA-RTWOA / DASUL	+2–5 %
Energy efficiency	FLA-RTWOA / QLAMSR	+5–10 %
Network lifetime	QLAMSR	+5–10 %
Data delivery rate	RDEANTN / MANAL	+2–5 %
Coverage area	MANAL	+5–10 %

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8. Data availability statement:

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

CRediT authorship contribution statement

R. Juliana: Conceptualization, Writing – original dr, aft. **Vignesh Janarthanan:** Project administration, Methodology. **M. Umamaheswari:** Writing – review & editing. **S. Sasikanth:** Visualization.

6. Ethics Approval and Consent to Participate

No participation of humans takes place in this implementation process.

Human and Animal Rights:

No violation of Human and Animal Rights is involved.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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