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Research paper

Deep Learning-Based Reduction of Computational Overhead and Energy Consumption in IoT-Assisted WSNs

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Abstract

Localization of Internet of Things-assisted Wireless Sensor Networks has gained significant interest from the research community. The key issues of energy consumption and computational overhead in existing studies are addressed by proposing a deep learning-based method to reduce both in the Internet of Things-assisted Wireless Sensor Networks presented here. Network topology is built using the topographic network framework to optimize energy use and computational efficiency. Anchor node deployment is performed using the Upgraded Butterfly Backtracking Optimization (UBBO) algorithm. Pilot agents are responsible for clustering sensor nodes with the Enhanced Density Peak Clustering Algorithm (E-DenPeC), which solves device heterogeneity and orientation issues through bias regression. For clustered sensor nodes, localization is carried out using the Squeeze-Excitation Network embedded Skip Connection Gated Recurrent Unit and Accelerated Iterative Algorithm (SEN-GRU-AI), based on five different measurement techniques (FLMT). Finally, collaborative localization is achieved through deep learning technology by reducing energy consumption and computational overhead. The results show that the proposed method surpasses existing approaches.

Keywords: *Wireless Sensor Networks (WSN); Internet of Things (IoT); Localization, Deep learning; Gated Recurrent Unit (GRU); Clustering, Upgraded Butterfly Backtracking Optimization algorithm.*

1. Introduction

The advancement of communication, embedded computer systems, and sensor technologies paved the way for Wireless Sensor Networks in a variety of applications, including environmental monitoring, defense surveillance, target tracking, user positioning, natural disaster and salvage, hazard detection, e-health care, crop monitoring, and more. [1]. The IoT devices embedded with sensors form the WSN. The wireless sensor network is an evolving technology that plays a vital role in our daily lives. Positioning is the primary process in WSNs that identifies the location of sensor nodes. The data we acquire without location information will be of no use at all. This makes localization essential in WSN and its related Internet of Things. In WSN, both anchor nodes and sensor nodes are involved. Anchor nodes are equipped with a Global Positioning System (GPS), and their locations are known. Since sensor nodes are numerous, integrating GPS technology with them results in high implementation costs and increased energy consumption.

Hence, localization of sensor nodes is performed using different measurement techniques. Over the past decade, estimating the accurate location of sensor nodes has been very challenging and is at its peak. There are two main types of localization measurement techniques: range-based techniques and range-free techniques. The range-based techniques commonly measure the distance between the sensor node and the anchor node. To localize the node, there are five different localization range-based measurement techniques, namely Angle of Arrival (AoA), Angle Difference of Arrival (ADoA), Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Received Signal Strength (RSSI) [2]. On the other hand, range-free techniques do not depend on distance but rely on hop counts, centroid, and geometrical information. Compared to range-based localization, range-free methods offer less accuracy. In range-based localization, accuracy is significantly affected by the placement of anchors, especially when there is no Line of Sight (LOS). Therefore, many studies deploy anchor nodes in a LOS manner to reduce multipath effects and fading. Additionally, network topology and device heterogeneity also impact localization accuracy.

For that reason, range-based techniques attract more attention for achieving greater accuracy in localization. The unproductive use of localized information hampers the further localization process in previous works. Hence, by considering all these perspectives, we have proposed a new concept that combines deep learning with the sensor node localization process to facilitate further advancements. Additionally, we have employed optimization algorithms to enhance the effectiveness of sensor node localization. The main goal of this proposed work is to adaptively and accurately locate unknown sensor nodes by simplifying the localization process collaboratively. The performance is evaluated based on energy consumption and computational overhead relative to the number of nodes.

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2. Research Contribution

An energy-efficient and low computational overhead intelligent localization technique is proposed in this work to enhance the resiliency of the IoT-assisted WSN environment. Some of the significant contributions of this work are listed below,

- The issues of connectivity, energy consumption, and computational overhead are addressed through the proposed network topology construction. To the best of our knowledge, based on the references, this is the first work to introduce a topology construction in a localization scenario using B-NET based on the anchor node range.
- To address multipath fading and path loss effects during localization, we perform LOS-aware anchor node placement using the UBBO algorithm based on several metrics. Implementing LOS-aware anchor placement reduces delayed transmission and communication overhead.
- The issue of unwanted energy consumption and reduced sensor node lifetime is addressed through heterogeneity and orientation-aware clustering using the E-DenPeC algorithm. In this process, the challenges of heterogeneity and orientation are mitigated with the B-NET bias regression method.
- Finally, the localization is achieved by using the SEN-GRU-AI based FLMT technique, which employs AOA, ADOA, TOA, TDOA, and RSSI measurements for robust localization. Collaborative localization is accomplished by selecting already localized nodes as sub-anchors, and results are continuously updated using deep learning technology.

3. Literature Review

This section reviews research on localization techniques in the IoT-assisted WSN environment using deep learning and optimization-based range and range-free methods. The brief overview of existing literature is provided below.

The authors in this research work [3], have proposed a framework focused on localizing wireless sensor nodes using a range-based measurement technique. Here, the signal received (RSSI) from the anchor node was considered, and the unknown nodes were localized with the help of an optimization algorithm called the Most Valuable Player. Meanwhile, in this study, routers acted as the anchor nodes, while user devices functioned as the unlocalized sensor nodes. Initially, the relationships between distance and received signal strength were determined using a nonlinear regression function. Then, the mentioned metaheuristic approach was applied to obtain the x and y coordinates. In this research, only the RSSI single technique was considered, which limits localization accuracy. Additionally, the lack of obstacle consideration during anchor placement leads to multipath effects and path loss.

An improved metaheuristic algorithm-based wireless sensor node localization was introduced in this work [4], by transferring the localizing problem into an optimization problem. At the time of network construction, anchor nodes were allocated an identity and propagated this identity to all the unlocalized sensor nodes. Once a node is localized, it is assumed to be a sub-anchor node for localizing other sensors. The sensor and anchor nodes were randomly deployed, which limits localization processes in terms of multipath fading due to the existence of obstacles. Also, ineffective sub-anchor selection without considering their energy, velocity, etc. results in localization errors. Localized information is unproductively utilized every time, so it increases computational overhead and energy consumption.

In this work [5], the authors have used enhanced particle swarm optimization (PSO) to localize unknown sensor nodes. They introduced a process called sensor node segmentation with PSO to improve localization accuracy. Initially, segmented nodes were also used to measure the shortest path and distance. The propagation of location information and RSSI signals from anchor nodes helps unlocalized sensor nodes estimate their distance using the centroid positions. Finally, the PSO algorithm was employed to determine the precise location of sensor nodes. Due to segmentation, this approach requires deploying additional anchors, which increases energy consumption and costs. Additionally, irregular topology construction reduces network coverage and hampers localization success rate and computational efficiency. Consequently, this leads to decreased performance in localization tasks.

To obtain optimal output, an iterative algorithm was applied in this work. [2], namely majorization and minimization. Localization techniques were determined using an estimation called the supreme likelihood. For each measurement, weights were allocated according to the Cramer-Rao Bound, which assigns weights based on short and long-range to enhance localization estimation. Here, anchor node deployments were performed ineffectively. By doing so, it can ruin the localization success ratio and supreme accuracy due to signal reflection and redundancy.

In this research work [6], an improved krill herd optimization algorithm and trilateration location measurement technique were used for sensor node localization. Initially, the trilateration localization technique was used to localize the unlocalized sensor node based on the anchor node's position and the distance between the sensor and the anchor node. The disengagement of localized sensor nodes leads to additional sensor nodes. In this manner, it increases implementation cost.

In this paper [7], the authors have introduced a framework for wireless sensor node localization in an indoor environment using an artificial neural network and range-based measurement. To overcome the localization shortcomings caused by some obstacles, such as furniture, link quality, temperature, and humidity, this work also considered these factors, along with received signal strength for estimating the distance between the sensor and the anchor node. Here, an artificial neural network is used to calculate the location of unknown sensor nodes. However, the utilized algorithm requires enormous computational power, hence it increases energy consumption.

The rise of IoT and 5G communication technology creates numerous research opportunities. However, compared to fifth-generation technology (5G), sixth-generation (6G) technology offers broader network coverage, ubiquitous connectivity, and greater reliability [8]. A comprehensive review of AI, ML, and reinforcement learning in WSNs, emphasizing applications in routing, node deployment, synchronization, and cross-layer optimization—all focused on enhancing energy efficiency and extending network lifespan [9].

In this work [10], the location of an unknown node was determined using a metaheuristic algorithm called Grey-Wolf Ant-Lion, combined with a recurring model that utilizes the fitness function. The authors randomly placed nearly 2K IoT sensor nodes. They localized the nodes based on the angle of arrival of the unlocalized sensor nodes. Here, localization is achieved with the help of a heuristic and recurrent model. However, the lack of consideration for the line of sight reduces the localization effectiveness.

In this research paper [11], a group coaching-based optimization algorithm was utilized to identify the location of unknown sensor nodes by reducing localization errors and enhancing accuracy. The anchor nodes estimate the location of unknown sensor nodes using the mentioned optimization algorithm. To obtain the location of sensor nodes, the algorithm uses a fitness function based on distance measurements. Here, the absence of aiding the help of localized sensors increases latency and energy consumption.

The authors [12], have localized the sensor nodes without the involvement of anchor nodes by considering base stations. Primarily, the sensor node localization issue is addressed as an optimization problem. This research work contemplates three major processes namely sorting of line of sight & non-line of sight, range calculation, and sensor node localization. For sorting line of sight and non-line of sight

and range calculation, an optimized DNN (deep neural network) was considered. For localizing the sensor nodes, distance (range) is only considered in this work. But it is insufficient for achieving high precision in sensor node localization.
In this research [13], wireless sensor node localization, which faces issues such as non-line-of-sight and high energy consumption, was addressed. The authors introduced two approaches: non-line-of-sight mitigation and sensor node selection to improve localization performance. Sensor node selection aimed to reduce energy consumption by allocating the best anchor node based on link quality. Localization efforts focused on reducing energy use and mitigating non-line-of-sight problems. However, the heterogeneity and orientation of sensor-embedded devices were not considered, which limits localization accuracy.
In this work [14], the authors introduce a concept that combines the range-based localization technique (Angle of Arrival) with effective weighted least squares to localize wireless sensor nodes. Two progression-based least-squares methods were used—one in a three-dimensional space and considering the variance of error. The localization errors were expressed as SD (standard deviation). Finally, these errors were used to approximate the positions of unknown nodes. The sensor and anchor nodes were positioned in a 3D space. However, the lack of topology construction limits network coverage and localization accuracy.
In this research paper [15] sensors that use invisible light (infrared) were localized using one of the measurement techniques, namely, the angle of arrival. In this work, a supermarket was considered as an indoor environment where carts were localized. Therefore, carts served as wireless sensor nodes embedded with infrared technology. For cart localization, signals emitted by the carts and their angles of arrival were analyzed by a server. However, the localized information is underutilized, which increases energy consumption and computational overhead.
A detailed review is presented of IoT devices embedded with sensors forming the WSN. [16]. The rise of IoT and 5G communication technology creates numerous research opportunities. However, compared to fifth-generation technology (5G), sixth-generation (6G) technology offers broader network coverage, ubiquitous connectivity, and greater reliability. [8]. Wireless sensor networks are among the emerging technologies that play a vital role in our daily lives. Positioning is a crucial process in WSNs, where the location of sensor nodes is determined. Data without location information is essentially useless. [17], [18]. A deep learning-based optimization model specifically for LoRaWAN sensor networks, improving performance and energy efficiency through DL-augmented decision-making at the network edge [19]. Recent research presents a co-design system for energy-harvesting WSNs, coordinating local inference and feature compression to reduce communication overhead while preserving accuracy [20].

4. Problem Formulation

The goal of IoT-assisted WSN localization is to accurately find the position of unknown sensor nodes using various range-based methods while minimizing energy use and computational load. Consider an m-dimensional IoT-assisted WSN with L anchor nodes and several unknown nodes. (i.e., unlocalized nodes) in 3D space (x, y, z). The position of the j^{th} an anchor node is defined as $an_j = \left[an_{xj}, an_{yj}, an_{zj}\right]^T \in \mathbb{R}^l, j \in L \triangleq \{1, \dots, L\}$. On the other hand, the unknown sensor node positions are shown as $O = \left[O_x, O_y, O_z\right]^T \in \mathbb{R}^l$. In general, the unknown sensor node within the two-mode anchor node transmission range is considered localized. During localization every O computes the distance in terms of NLOS from the anchor node that can be formulated as,

$$dis_{NLos} = dis_i + no_i + err_{NLos} \tag{1}$$

Where, dis_I is the distance calculated by the i-th unknown sensor node, err_{NIos} is the error during NLOs, and no_i denotes the Gaussian noise. The anchor node continuously transmits a signal within its transmission range. The unknown sensor node receives the signal information and measures the path loss (PL) using various measurement techniques. Let the j-th anchor node measure the range information with different measurement methods, which can be formulated as,

$$RSSI \rightarrow PL_j = PL_0 + 10\gamma\log_{10}\|O - an_j\| + no_{RSSI_i} \tag{2}$$

From the above equation, no_{RSSI_i} indicates the RSSI noise, the exponent of path loss is denoted as γ, and PL_0 denotes the path at reference distance dis_j. The AOA and ADOA measurement for the j-th anchor node can be formulated as,

$$AOA \rightarrow \begin{cases} \emptyset_j = \tan^{-1}\left(\frac{O_y - an_{yj}}{O_x - an_{xj}}\right) + no_{AOA_j} \\ \theta_j = \cos^{-1}\left(\frac{O_z - an_{zj}}{\|O - an_j\|}\right) + no_{AOA_j} \end{cases} \tag{3}$$

$$ADOA \rightarrow \begin{cases} \emptyset_{(j-2\pi)} = \tan^{-1}\left(\frac{O_y - an_{yj}}{O_x - an_{xj}}\right) - \|O\| + no_{AOA_j} \\ \theta_{(j-2\pi)} = \cos^{-1}\left(\frac{O_z - an_{zj}}{\|O - an_j\|}\right) - \|O\| + no_{ADOA_j} \end{cases} \tag{4}$$

From equations (3) and (4), $\emptyset_j$ and θ_j define the azimuth and elevation angles, $\emptyset_{(j-2\pi)}$, and $\theta_{(j-2\pi)}$ represent the azimuth and elevation delay angles for ADOA measurements. The noise in the AOA and ADOA is denoted as no_{AOA_j} and no_{ADOA_j} respectively. The TOA and TDOA measurements for the j-th anchor can be formulated as,

$$TOA \rightarrow ct_j = \|O - an_j\| + no_{TOA_j} \tag{5}$$

$$TDOA \rightarrow c(t_j - t_0) = \|O - an_j\| - \|O\| + no_{TDOA_j} \tag{6}$$

Where,no_{TOA_j} and no_{TDOA_j} denotes the noises in the time measurement.
However, using five different measurements for node localization creates a majorization minimization problem, which can be overlooked by focusing on some of the objectives through minimization and maximization. The objectives are listed as follows,

$$\text{mini} \rightarrow \{\text{Ene}, \text{Cost}, \text{loc}_{\text{err}}\} \quad (7)$$

Where equation (7) represents the minimization of energy consumption, cost, and error during localization, respectively.

5. Proposed Work

The problems discussed earlier and the proposed research address the outlined objectives. First, we built the network topology as a Voronoi structure to improve connectivity and coverage using the B-NET algorithm. In this network, anchor nodes are deployed with awareness of LOS and NLOS conditions through the UBBO algorithm, which is based on multiple metrics. After establishing the initial population, the algorithm evaluates each butterfly's position by calculating the fitness function. Once the anchor nodes are effectively placed, the work aims to enhance localization accuracy by clustering with the E-DenPeC algorithm, which considers heterogeneity and orientations.
Following clustering, unlocalized nodes are localized using SEN-GRU-AI, which employs five different Localization Measurement Techniques (FLMT), such as AOA, ADOA, TOA, TDOA, and RSSI. Additionally, the non-convex, non-smooth problem caused by range measurement is addressed through a majorization-minimization iterative algorithm. Finally, deep learning technology is used to facilitate collaborative localization by selecting sub-anchors based on various metrics.
Figure 1 illustrates the overall architecture of the proposed deep learning-based approach to reduce CO and EC in the IoT-assisted WSN localization model. The entities involved in the proposed architecture include intelligent anchor node placement using the UBBO algorithm, sensor network construction with B-NET, clustering achieved through E-DenPeC, and deep learning localization utilizing FMLT and SEN-GRU-AI mechanisms. To ensure robust and accurate localization results, we have outlined four major advancements: Topology Construction, LoS-aware Anchor Nodes Deployment, Density-based Clustering & Heterogeneity Handling, and Deep Learning-assisted Collaborative Localization.

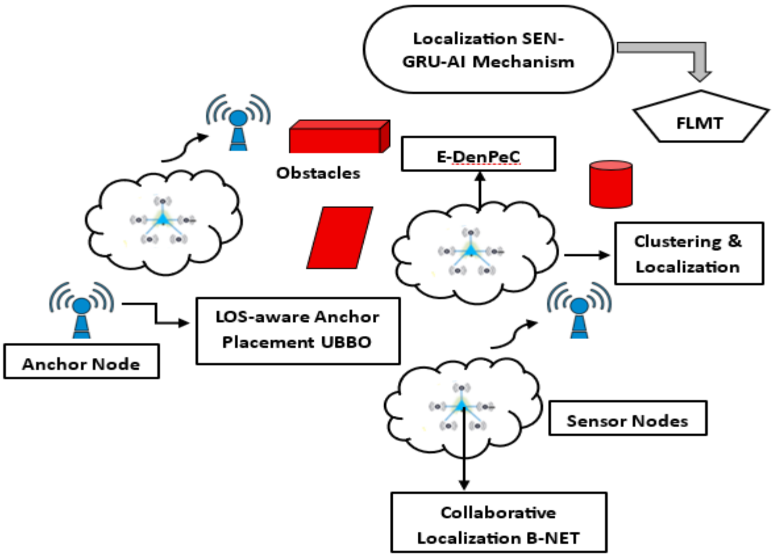

Fig.1: Architecture of the Proposed Work

This work focuses on localizing unknown IoT-assisted wireless sensor nodes using deep learning to decrease computational overhead and energy consumption. The energy dissipated by the anchor node is utilized to improve the power amplifiers and radio electronics systems. Meanwhile, the energy used by sensor nodes (both localized and unlocalized) powers the radio system equipment. The energy model applies to both free space and multi-path fading channels. The energy consumed during transmission within the transmission range can be expressed as,

$$\text{Ene}_{\text{tx}}(\text{dis}, \text{b}) = \text{bEne}_{\text{ele}} + \text{b} \in \text{dis}^{\beta} = \begin{cases} \text{bEne}_{\text{ele}} + \text{b} \in 8^{\text{F}^2} \\ \text{bEne}_{\text{ele}} + \text{b} \in \text{amp}^{\text{F}^4} \end{cases} \quad (8)$$

Where, dis represents the distance between the anchor and sensor nodes, b is the packet it sends, Ene_{ele} defines the electronic energy factor, which depends on aspects such as modulation and digital coding. The 8^{F^2} and amp^{F^4} denotes the energy of the amplifier, which is based on the transmission distance and the bit error rate. Conversely, the reception energy consumption at the sensor node radio can be formulated as,

$$\text{Ene}_{\text{rx}}(\text{b}) = \text{bEne}_{\text{ele}} \quad (9)$$

Topology construction is essential for achieving accurate results in localization because we built the topology using the ToPoNET framework. This framework is supported by a Voronoi structure and is developed using the B-NET algorithm. Typically, the Voronoi diagram based on networks replaces traditional planes with real-time network spaces (e.g., test area, road area). The distances between real-time entities are defined by the shortest path between them, which also replaces conventional measures. The formulation of the network-based Voronoi diagram can be expressed as,

$$\text{Vor} = \{\text{Vor}_1, \text{Vor}_2, \ldots, \text{Vor}_n\} \quad (10)$$

From the above equation, Vor_1 is represented by $\{\text{Pl}|\text{dis}(\text{pl}, \text{pl}_1) \leq (\text{pl}, \text{pl}_2)\}$; $\text{dis}(\text{pl}, \text{pl}_1)$ from which the $\text{Pl} = \{\text{Pl}_1, \text{Pl}_2, \ldots, \text{Pl}_n\}$ that is termed as generator points on the network space, the pl_1 is termed as a subjective point, and the distance between a subjective and arbitrary point can be defined as $dis(pl, pl_1)$. The proposed B-NET-based Voronoi consists of three phases: booting, anchor nodes properties computation, and Voronoi construction.

After constructing the network, anchor nodes are thoughtfully deployed in an IoT-assisted WSN environment. Sensor node localization is significantly impaired by Non-Line of Sight (NLOS) issues. If an anchor node is placed where obstacles exist, it falls under NLOS. Therefore, Line of Sight (LOS) is crucial for achieving accurate node localization. However, several constraints limit achieving a clear line of sight. To address this, we have optimally placed the anchor nodes using the UBBO algorithm, considering obstacles (size and shape), terrain, signal propagation, delay, distance, link quality, and path loss. The cherry-picked UBBO algorithm has been enhanced in accuracy and convergence rate by adding guiding weights to the global search. Additionally, the backtracking approach effectively finds all possible paths by removing non-optimal solutions. Therefore, this combination of backtracking and the improved butterfly optimization algorithm ensures the best line of sight.

The UBBO algorithm starts by generating a population of butterflies, each representing a potential solution for anchor node placement. These butterflies explore the search space, guided by the intensity of a fragrance that symbolizes the objective function values—such as signal strength, path loss, and interference levels. In our work, the static anchor nodes are considered as butterflies that have the unique properties of features mentioned above for optimal LOS-aware placement. Initially, the location of the anchor nodes needs to be initialized. In the Dim dimensional space of M anchor populations, each position of the anchor can be represented in vector format as $y_{i,j} = [y_{i,1}, y_{i,2}, \dots, y_{i,Dim}]$. The position of the anchor node can be formulated as,

$$y_{i,j} = RAN \times (Up^b + Lo^b) + Lo^b \tag{11}$$

From the above equation, $i \in \{1,2,\dots,pop\}, j \in \{1,2,\dots,Dim\}$ in which the $y_{i,j}$ denotes that the i-th anchor is in the j-th dimensional space. The RAN denotes the random of interval (0,1), whereas the Lo^b and Up^b denotes the lower and upper boundaries, respectively.

To improve the avoidance of local optima, the population restart method is used to reduce the unwanted population. The probability of population reduction can be expressed as,

$$pr^{ele} = RAN \times \left(\forall + \frac{C}{pop}\right) \tag{12}$$

From the above equation, $\forall$ and C represents the solutions of the global optimum, and pr^{ele} represents the population that will be disregarded. From that, the new formula for population can be formulated as,

$$y_j^{t+1} = RAN \times (Up^b - Lo^b) + Lo^b \text{when } RAN < pr^{ele} \tag{13}$$

From the above equation, it is noted that the y_j^{t+1} represents the vector solution of the j-th anchor at the t+1 iteration.

The factors influencing the placement of anchor nodes are called the Selectness Factor (SF), which can be formulated as:

$$SF = {fa_{ors}}^{\aleph} \tag{14}$$

Where, fa_{ors} represents the factors/metrics of the anchor nodes, and $\aleph$ defines the constant parameter set [0,1]. With the help of SF, the proposed UBBO started its searching process. The proposed UBBO applied supervisory weight information to the global search ability of UBBO to enhance its overall search performance. The formulation of supervisory weight can be provided as,

$$Su^{we} = maxi_{we} - (maxi_{we} - mini_{we}) * {}^{iter}/_{max_{iter}} \tag{15}$$

Where, $iter$ denotes the iteration, max_{iter} denotes the maximum iteration, Su^{we} is the supervisory weight, $maxi_{we}$and $mini_{we}$ denotes the maximum and minimum value of weight, respectively.

The weighted global search requires new population formula that can be provided as,

$$y_j^{t+1} = Su^{we} \times y_j^t + (RAN^2 \times \beth^* - y_j^t) \times SF_i, RAN < Pr \tag{16}$$

Where, Su^{we} is the supervisory weight at the j-th iteration, $y_j^{t+1}$and y_j^t represents the vector solution of j-th anchor node at the t+1-th and t-th iteration, $\beth^*$ is the recent global optimum,SF_i is the selectiveness factor, and Pr is the global search probability. When the probability favors to high, the local corruption phase came into picture which also based on the new population formula as,

$$y_j^{t+1} = y_j^t + (RAN^2 \times y_i^t - y_r^t) \times SF_i, RAN \geq Pr \tag{17}$$

The local corruption phase happens in the designated area within the WSN environment when all other areas are occupied by anchor nodes. From the above equation, the y_r^t and y_i^t denotes the other anchors in the population. Once completed the global search and local corruption, the proposed work adopted backtracking method to effectually finds all the possible paths by eliminating the non-optimal solutions. The pseudocode provides the UBBO-based LOS-aware anchor node placement algorithm.

Initialize the objective function. $y_{i,j} = [y_{i,1}, y_{i,2}, \dots, y_{i,Dim}]$
Obtain initial population for pop anchors. $y_i \in \{1,2,\dots,pop\}$
Perform population alleviation (12)
Get new population (13)
Whilemax_{iter} not reached **do**
For every an^j in the y_j**do**
Compute SF using (14)
End For
// Find the LOS position//
For every an^j in the y_j**do**
Create and RAN [0,1]
If RAN $< Pr$**then**
Assign Su^{we} for global search (15)
Place the anchor in best LOS links (16)
Else
Select random best LOS links (17)
End If
End For
Perform backtracking for selecting effective solutions
End While

Pseudocode for UBBO-based anchor node placement algorithm

Later, the optimal deployment of anchor nodes involves clustering sensor nodes by the pilot agent to reduce energy consumption and improve localization accuracy using E-DenPeC. The mentioned algorithm is enhanced by adding a robust sparse search that decreases computational complexity by limiting the number of similarity calculations needed to generate decision graphs. Based on these decision graphs, cluster centers are identified quickly. Let the sensor nodes in the environment be expressed as $O = \{o_1, o_2, \dots, o_n\} \in \mathcal{R}^{Dim \times q}$. From the sensor nodes, the sensor node similarity is computed based on device heterogeneity and their orientations using Euclidean distance which can be formulated as,

$$dis_{ji} = \sqrt{(o_j - o_i)^2} \tag{18}$$

The sequence for a distance is represented as $dis = [dis_{o_1,o_f}, dis_{o_2,o_f}, \dots, dis_{o_n,o_f}]$ from which the o_f represents the random point. the similarity matrix construction for the 10-sensor node $O' = [O'_1, O'_2, \dots, O'_{10}]$ in the proposed environment can be limited only by computing the similarities

$$sim_{mat} = \begin{bmatrix} \{dis_{12}, dis_{13}, dis_{14}, dis_{23}, dis_{24}, dis_{34}\}, \\ \{dis_{25}, dis_{35}, dis_{45}\} \\ \{dis_{36}, dis_{46}, dis_{56}\} \\ \{dis_{47}, dis_{57}, dis_{67}\} \\ \vdots \\ \{dis_{7,10}, dis_{8,10}, dis_{9,10}\} \\ \end{bmatrix} \tag{19}$$

Upon constructing the similarity matrix, the local density (ζ_j) and comparative parting (η_j) are computed to update the similarity matrix. The pseudocode of the E-DenPeC Algorithm demonstrates the proposed density-based clustering and heterogeneity management.

Input: Sensor Nodes ($O = \{o_1, o_2, \dots, o_n\}$)
Output:sim_{mat}, similarity matrix and clustering
Begin
Compute dis_{ji} for O, distance between i and j nodes (18)
Rearrange sensor nodes based on the dis_{ji} from low to high
// Similarity Matrix Construction//
For j=1 (step 0.4n-1) **do**
Compute dynamic Euclidean measurements for O
Construct sim_{mat} , similarity matrix (19)
Update sim_{mat} using ζ_j and η_j, the local density (ζ_j) and comparative parting (η_j)
Filter outliers
End For
Estimate bias regression based on B-NET
End

Pseudocode for E-DenPeC clustering algorithm

The conventional majorization-minimization limits have fewer convergence problems, but they result in higher computational complexity. To enhance convergence and decrease computational complexity, the Anderson acceleration is adopted, which utilizes the present state. (y^k) and n-number of predecessor states $(y^{k-1}, \dots, (y^{k-n}))$ to calculate accelerated iteration based on an affine combination as,

$$y_{AA} = Aff(y^k) - \sum_{i=1}^{n} \emptyset_i^* \left(Aff(y^{k-i+1}) - Aff(y^{k-I})\right) \tag{20}$$

Where, y_{AA} is the accelerated function by the Anderson method, and Aff (.) is the affine transform combination.

Once the pilot agent localizes the sensor node, it is communicated to the key agent, who selects a sub-anchor node to enable collaborative localization when multiple conditions, such as energy, behavior, trajectory, and velocity, are met. The sensor node that holds the initial position is elected as the cluster head. Additionally, with the assistance of sub-anchor nodes, other unlocalized sensor nodes are localized. The steps involved in deep learning-based collaborative localization are as follows.

Step 1: With the coordination of the location resource management locomotive, the sub-anchors tend to train their local model (i.e., localized information) by downloading copies of parameters of the global model from the location resource management locomotive.

Step 2: Then, the local resource management locomotive selects the sets of clients (i.e., sub-anchors) for each iteration and conducts deep learning rounds.

Step 3: Once the local model $f_j(k)$, is updated to the location resource management locomotive, it performs aggregation of acquired local models based on the objective function.

Step 4: Finally, the loss function is calculated based on the client's local model to reduce training time. The process will continue for several iterations until the desired performance is achieved. The pseudocode for the deep learning based collaborative location algorithm is provided below.

Set Global Model Parameters
For every round (k=1,2,…) **do**
  Select random clients
For each clients local models **do**
    Update→ data samples
Generate Global Models
End For
End For
Sub-Anchor Node:
For every $S_{an} = \{S_{an1}, S_{an2}, \dots, S_{anN}\}$**do**
  Update Local Model → Global Server
  Update Local models
End for
Pseudocode for deep learning localization algorithm

6. Experimental Results

This section presents the implementation and comparative analysis of the proposed method. It also provides a detailed quantitative comparison of the results.

A. Simulation Setup

The proposed method aims to enhance localization accuracy while reducing energy consumption and computational overhead. The process is tested and simulated using Network Simulator 3.26 (NS-3.26). To obtain more precise simulation results, we have adjusted the setup as detailed in Table 1. The simulation involves five anchor nodes, 35 sub-anchor nodes, and 50 unlocalized nodes within a 250x250 meter area.

Table 1 Simulation Settings

Simulation Parameters	Values
# of Anchor Nodes	5
# of Unlocalized Nodes	50
# of Sub-Anchors	35
Simulation Environment	$250 \times 250\text{m}^2$
Signal Propagation Range	500m (all directions)
Energy Consumption During Transmission	1.75W
Energy Consumption During Reception	0.5W
Initial Energy Consumption	50J

B. Comparative analysis

This section presents a comparative analysis of the proposed method with existing works, such as RSSI-MVPA (Most Valuable Player Algorithm) [3] and ECSA (Enhanced Cuckoo Search Algorithm) [4], focusing on metrics like energy consumption and computational overhead.

1) Comparison of Energy Consumption

The energy consumption refers to the amount of energy used by the IoT-WSN nodes in the environment during the localization process. The Energy Consumption (EC) can be expressed as,

$$\mathrm{EC} = \mathrm{ToT_{ene}} - \mathrm{Con_{ene}} \tag{21}$$

Where, $\mathrm{ToT_{ene}}$ is the total energy of the IoT-WSN nodes, and $\mathrm{Con_{ene}}$ is the consumed energy of IoT-WSN nodes.

As shown in Figure 2, the proposed work results in lower energy consumption. This reduction occurs because the proposed method performs clustering of IoT-WSN nodes based on device heterogeneity and orientation using the E-DenPeC algorithm.

Implementing clustering in the IoT-assisted WSN environment decreases the need for all nodes to transmit their signals directly to the anchors. The proposed approach selects a cluster head to send its data to the anchor nodes, thereby reducing unnecessary energy use of the IoT-WSN nodes and extending their lifetime. Conversely, the existing methods ECSA and RSSI-MVPA are limited by poor data transmission because they involve all WSN nodes transmitting data to and from the anchor nodes, which results in higher energy consumption and a shorter network lifetime. The numerical results show that the proposed approach achieves a lower EC as the number of nodes increases to 100, reaching 73J, while the existing methods result in higher ECs of 82J and 95J, respectively. Overall, the proposed approach reduces EC by 9J-22J compared to the existing methods.

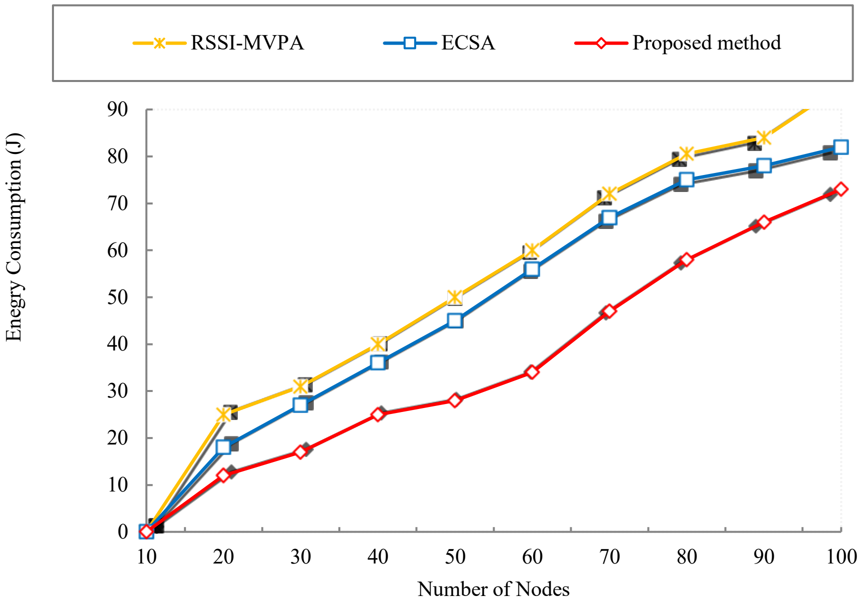

Fig. 2 Number of Nodes Vs Energy Consumption (J)

2) Comparison of Computation Overhead

The computation overhead is defined as the ratio of the data transmitted and received, in both amount and type, to the total number of IoT-WSN nodes in the environment. Mathematically, the formulation of Computation Overhead (CO) is expressed as,

$$\mathrm{CO} = \frac{\mathrm{Dat}_{\mathrm{tx/ty}}}{\mathrm{O_n}} \tag{22}$$

Where, $\mathrm{Dat}_{\mathrm{tx/ty}}$ denotes the data transmitted/type of data (i.e., heterogeneity), and $\mathrm{O_n}$ denotes the total number of sensor nodes in the environment.

The comparison of CO with the number of nodes for the proposed method and existing works, ECSA and RSSI-MVPA, is shown in Figure 3. From the figure, it is clear that CO increases as the number of nodes grows. Among them, our proposed method has a lower CO than the state-of-the-art approaches. The reason for this lower CO is that the proposed work performs heterogeneity and orientation analysis for the underlying WSN-IoT nodes using the majorization-minimization method.

By performing heterogeneity and orientation analysis, the complexity of computing the localization measurements is reduced in the proposed work, thereby achieving lower computational overhead. In contrast, the existing works fail to analyze the heterogeneity and orientation of the WSN nodes. Different devices possess different types of data, resulting in higher localization times and increased computational overhead in the existing works. Numerical analysis shows that the proposed work achieves a lower CO of 127 when the number of nodes reaches 100. In contrast, the existing works, ECSA and RSSI-MVPA, have higher computational overheads of 150 and 177, respectively. Overall, the difference in CO between the proposed and existing approaches ranges from 13 to 50.

The results clearly show that even after increasing node density and changing the environment, the proposed method effectively keeps CO and EC levels low.

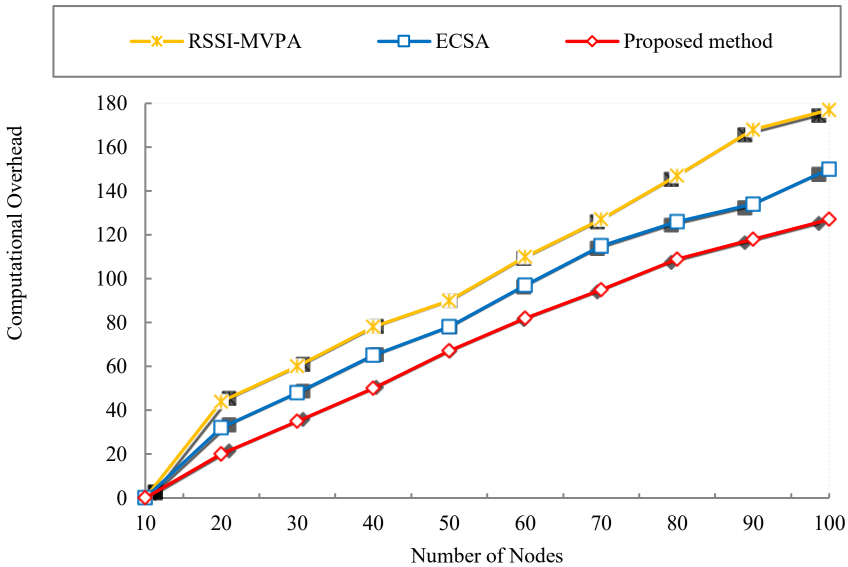

Fig. 3 Number of Nodes Vs Computation Overhead

7. Research Summary

This section briefly summarizes the experimental results. First, the network simulation implementation and its parameters are listed in Table 1. Additionally, the simulation results are presented in the comparative analysis section in Table 2, which verifies both the proposed and existing methods using several performance metrics shown through graphical representations in Figures 2 and 3.

- This work constructs an IoT-assisted WSN network topology using a Voronoi structure and the B-NET algorithm, enhancing representation while reducing computational complexity to achieve robust connectivity and network coverage considering the range.
- Intelligent anchor nodes were deployed in an LOS-aware manner by considering different features such as obstacles (size and shape), terrain, signal propagation, delay, distance, link quality, and path loss with the help of the UBBO algorithm which offers the best line of sight with high convergence rate and high precision.
- To reduce energy consumption and enrich the localization accuracy, sensor nodes are clustered using the E-DenPeC which degrades computational complexity.
- Eventually, deep learning is involved in our work to ease the localization process. Besides, five different localization measurement techniques are taken into account to achieve adaptability in localization using SEN-GRU-AI. Along with this, localized sensor nodes are wisely utilized to localize the unknown sensor nodes by considering essential parameters.

Table 2: Comparison of Average Results Between Proposed and Existing Methods

Performance Metrics	RSSI-MVPA	ECSA	Proposed method	Less Difference
Energy Consumption (J)	95	82	73	22-9
Computation Overhead (sec)	177	150	127	50-13

8. Limitations and Future Work

Limitations: Though the proposed method's performance is better than other existing work for low energy consumption and low computational overhead, there are some limitations of this proposed method, which are mentioned as follows.

- The deep learning components, particularly SEN-GRU-AI, require extensive and high-quality datasets for practical training. In real-world IoT-assisted WSN deployments, acquiring such datasets may be challenging due to environmental constraints and privacy concerns.
- While, the framework reduces computational overhead during operation, the training phase of deep learning models and optimization algorithms (e.g., UBBO, E-DenPeC) is computationally intensive and may require powerful processing units.
- Rapid changes in network topology, such as node failures or mobility, may affect localization accuracy since the model is primarily trained on relatively stable network configurations.
- Although the proposed method is designed for heterogeneous IoT-assisted WSNs, its performance may degrade in extremely large-scale deployments with tens of thousands of nodes unless further optimization techniques are employed.

Future work: This proposed research still has many areas for future exploration, which are listed as follows.

- Future research can focus on model compression, pruning, and quantization to reduce the memory footprint and computational requirements, making SEN-GRU-AI more suitable for ultra-low-power sensor nodes.
- Expanding the framework to incorporate security layers can protect against malicious localization attacks such as spoofing or Sybil attacks, which are increasingly relevant in IoT-assisted networks.
- Combining deep learning-based localization with other methods—such as visible light positioning (VLP)—could improve accuracy in complex indoor or multipath environments.
- Extending the proposed work to handle tens or hundreds of thousands of heterogeneous nodes while maintaining energy efficiency and low computational cost remains a promising area for research.

9. Conclusion

Higher energy consumption and computational overhead pose significant challenges in an IoT-assisted WSN-based localization environment. These issues are addressed through the implementation of the proposed DLR-COEC-WSN method to develop a resilient and intelligent localization framework. Initially, the proposed IoT-WSN network was thoroughly designed to resolve connectivity and coverage issues. The proposed approach uses the B-NET algorithm to build the network topology within a Voronoi structure based on the range of anchor nodes. After establishing the network, the anchor nodes are positioned optimally to address issues such as multi-fading, obstacles, energy consumption, and computational overhead. Once the anchor nodes are correctly placed, the pilot agent at each anchor node clusters the underlying sensor nodes to facilitate localization and reduce computational complexity.

The proposed deep learning framework significantly improves the operational efficiency of IoT-assisted WSNs by reducing energy consumption and computational load. This leads to longer network lifespans, better real-time responsiveness, and more effortless scalability in various real-world applications like smart agriculture, healthcare, industrial automation, and environmental monitoring. The overall simulation results demonstrate that the proposed localization method outperforms existing approaches in energy efficiency and computational cost.

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